

State of Florida



Impact of Incentive/Disincentive Specifications on Long-Term Asphalt Pavement Performance

FINAL REPORT

FDOT Contract Number: BE912

December 2022

**Submitted By:
Hyung S. Lee, Ph.D., P.E.
Hadi Nabizadeh, Ph.D.**



100 Trade Centre Dr., Suite 200
Champaign, Illinois 61820

DISCLAIMER

The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the State of Florida Department of Transportation.

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
AREA				
in ²	square inches	645.2	square millimeters	mm ²
ft ²	square feet	0.093	square meters	m ²
yd ²	square yard	0.836	square meters	m ²
ac	acres	0.405	hectares	ha
mi ²	square miles	2.59	square kilometers	km ²
VOLUME				
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft ³	cubic feet	0.028	cubic meters	m ³
yd ³	cubic yards	0.765	cubic meters	m ³
NOTE: volumes greater than 1000 L shall be shown in m ³				
MASS				
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
TEMPERATURE (exact degrees)				
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
ILLUMINATION				
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m ²	cd/m ²
FORCE and PRESSURE or STRESS				
lbf	poundforce	4.45	newtons	N
lbf/in ²	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	When You Know	Multiply By	To Find	Symbol
LENGTH				
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
AREA				
mm ²	square millimeters	0.0016	square inches	in ²
m ²	square meters	10.764	square feet	ft ²
m ²	square meters	1.196	square yards	yd ²
ha	hectares	2.47	acres	ac
km ²	square kilometers	0.386	square miles	mi ²
VOLUME				
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m ³	cubic meters	35.314	cubic feet	ft ³
m ³	cubic meters	1.307	cubic yards	yd ³
MASS				
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
TEMPERATURE (exact degrees)				
°C	Celsius	1.8C+32	Fahrenheit	°F
ILLUMINATION				
lx	lux	0.0929	foot-candles	fc
cd/m ²	candela/m ²	0.2919	foot-Lamberts	fl
FORCE and PRESSURE or STRESS				
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in ²

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.	
4. Title and Subtitle Impact of Incentive/Disincentive Specifications on Long-Term Asphalt Pavement Performance		5. Report Date	
		6. Performing Organization Code	
7. Author(s) Hyung S. Lee and Hadi Nabizadeh.		8. Performing Organization Report No.	
9. Performing Organization Name and Address Applied Research Associates, Inc. 100 Trade Centre Dr., Suite 200 Champaign, IL 61820		10. Work Unit No. (TRAIS)	
		11. Contract or Grant No. BE912	
12. Sponsoring Agency Name and Address Florida Department of Transportation State Materials Office 5007 N.E. 39 th Avenue Gainesville, FL 32609		13. Type of Report and Period Covered Draft Final Report December 2019 to December 2022	
		14. Sponsoring Agency Code	
15. Supplementary Notes			
16. Abstract <p>FDOT's Percent Within Limits (PWL) specification for acceptance and payment of asphalt materials was first implemented in 2002. The objective of this study was to determine the level of impact that FDOT's PWL specification has on the long-term performance of asphalt pavements.</p> <p>To meet this objective, Multinomial Logistic Regression Analyses (MLRA) were performed. The results indicated that FDOT's Composite Pay Factor (CPF) is cost-effective (i.e., the higher the CPF, the lower the probability of distresses). Moreover, it was shown that CPF has a profound effect on cracking and raveling of both dense and open graded mixtures. According to the results of MLRA, it is recommended that FDOT continue to use the AQC weights revised and implemented in 2019 for dense graded mixtures. For open graded mixtures, it is recommended that FDOT explore the option of increasing the weight of Percent Passing 3/8 Inch Sieve (PF_P3.8) by 5 percent and reducing the weight of Percent Passing No. 8 Sieve (PF_P8) by 5 percent.</p>			
17. Key Word Asphalt, Specification, Incentive, Disincentive, Percent Within Limits (PWL), Percent Deficient (PD), Pay Factor (PF), Composite Pay Factor (CPF)		18. Distribution Statement No restrictions	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 77	22. Price

EXECUTIVE SUMMARY

Historically, state highway agencies (SHAs) have used various Quality Assurance (QA) specifications for determining whether to accept or reject the product delivered by the contractors. Historically, many SHAs have adopted the average deviation from a target value as the measure of quality in the 1960s and 1970s. Over the years, SHAs realized that using the average deviation alone has limitations because it does not account for the variability of the construction material properties within a project. On the other extreme, variability alone as a quality measure can also be misleading as the entire project could have very low variability and high average deviation from the target value. As such, several quality measures that can incorporate both the average deviation and the variability of the quality characteristics have been recognized as better quality measures for QA specifications. The concept of Percent Within Limits (PWL) or Percent Defective (PD) is an example of such quality measures.

FDOT's PWL specification for acceptance and payment of HMA materials was first implemented in 2002, as part of the Department's Contractor Quality Control (CQC) system. The CQC system uses contractors' verified QC data for acceptance and payment. Another major difference between FDOT's new PWL specification and the old specification, is that the PWL system allows the contractors to earn incentives or disincentives depending on the quality of their material and pavement constructed. Since the implementation of the PWL in 2002, the QA specification has been refined several times based on research and feedback from industry before arriving at the current specification.

The basic premise of the incentive/disincentive specification based on the concept of PWL is that the long-term pavement performance is related to certain Acceptance Quality Characteristics (AQC's). However, such a relationship has not been defined or established based on FDOT's data. Due to the lack of such relationships, the quality characteristics and their weights currently implemented in FDOT's PWL specification were established empirically based on past experience and engineering judgement. As such, the primary objective of this study was to determine the level of impact that FDOT's PWL specification has on the long-term performance of asphalt pavements.

In this study, a Multinomial Logistic Regression Analysis (MLRA) was performed to assess the impact of FDOT's PWL specification on long-term asphalt pavements. The analysis results indicated that FDOT's Composite Pay Factor (CPF) is cost-effective (i.e., the higher the CPF, the lower the probability of distresses). Moreover, it was shown that CPF has a profound effect on cracking and raveling of both dense and open graded mixtures. Although the effect of CPF on rutting was minimal, rutting is not the predominant distress in Florida.

The results of additional logistic simulation for dense graded mixtures indicated that FDOT's new weights implemented in their 2019 specification reduce the probability of long-term cracking and raveling significantly compared to the original weights in the 2002 specification. As such, it is recommended that FDOT continue to use the new AQC weights implemented in 2019.

As for open graded mixtures, although FDOT's AQC weights implemented in 2002 (and still being used) are cost-effective, the results indicated that the probabilities of cracking and raveling can be reduced further. Therefore, it is recommended that FDOT explore the option of increasing the weight of Percent Passing 3/8 Inch Sieve (PF_P3.8) by 5 percent and reducing the weight of Percent Passing No. 8 Sieve (PF_P8) by 5 percent, in accordance with the MLRA results.

TABLE OF CONTENTS

Disclaimer	ii
Executive Summary	v
Table of Contents	vii
List of Figures	x
List of Tables	xii
1. Introduction.....	1
1.1. Background	1
1.2. Research Objectives	2
2. Literature Review.....	3
2.1. Introduction	3
2.2. Quality-Based Pay Adjustment System	3
2.2.1. Acceptance Quality Characteristics (AQC)s	4
2.2.2. Quality Measures (QMs).....	6
2.2.3. Pay Factor	9
2.2.4. Composite Pay Factor (CPF)	11
2.2.5. Operating Characteristic (OC) and Expected Pay (EP) Analyses	12
2.3. Performance-Related Specifications (PRS)	14
2.4. Development of Quality-Based Pay Adjustment System	15
2.4.1. Engineering-based Methods.....	16
2.4.2. Empirical-based Methods	18
2.4.3. Experience-based Methods	21
2.5. Overview of FDOT’s Incentive/Disincentive Specification	21
2.6. Overview of SHA Practice	23
2.6.1. Practice of Select SHAs for Acceptance of Open Graded Friction Course (OGFC)	25
2.7. Summary	30
3. Data Gathering	31
3.1. Introduction	31
3.2. Data Elements	31
3.2.1. Pay Factor Data.....	31
3.2.2. Mix Design Data.....	36
3.2.3. Traffic Data.....	36
3.2.4. Distress Data	36

3.3. Comprehensive Database	40
4. Preliminary Analysis and Challenges	42
4.1. Project Level Analysis	42
4.2. Network Level Analysis.....	44
5. Logistic Regression for network level analysis	49
5.1. Multinomial Logistic Regression for Cracking.....	49
5.2. Multinomial Logistic Regression for Rutting	53
5.3. Multinomial Logistic Regression for Raveling.....	55
5.4. Logistic Analysis Summary and Discussion.....	58
6. Development of Recommendations	61
6.1. Summary of Logistic Regression	61
6.2. Logistic Simulation	61
6.2.1. Assumptions and Limitations	62
6.2.2. Simulation Scenarios	62
6.3. Logistic Simulation Results	64
6.3.1. Dense Graded Mixtures	64
6.3.2. Open Graded Mixtures.....	66
6.4. Summary of Recommendations	69
7. Summary and Conclusions	71
8. References.....	73
Appendix A: Review of SHA Practices.....	78
Appendix B: Project Level Correlations CPF vs Cracking for Dense Graded Mixtures.....	88
Appendix C: Project Level Correlations CPF vs Rutting for Dense Graded Mixtures	103
Appendix D: Project Level Correlations CPF vs Raveling for Dense Graded Mixtures.....	118
Appendix E: Project Level Correlations CPF vs Cracking for Open Graded Mixtures	133
Appendix F: Project Level Correlations CPF vs Rutting for Open Graded Mixtures	143
Appendix G: Project Level Correlations CPF vs Raveling for Open Graded Mixtures.....	153
Appendix H: Multinomial Logistic Analysis Figures for Cracking of Dense Graded Mixtures	163
Appendix I: Multinomial Logistic Analysis Figures for Cracking of Open Graded Mixtures...	167
Appendix J: Multinomial Logistic Analysis Figures for Rutting of Dense Graded Mixtures....	171
Appendix K: Multinomial Logistic Analysis Figures for Rutting of Open Graded Mixtures....	175
Appendix L: Multinomial Logistic Analysis Figures for Raveling of Dense Graded Mixtures	179
Appendix M: Multinomial Logistic Analysis Figures for Raveling of Open Graded Mixtures.	183
Appendix N: Simulated Probability Curves for Cracking of Dense Graded Mixtures.....	187

Appendix O: Simulated Probability Curves for Rutting of Dense Graded Mixtures	198
Appendix P: Simulated Probability Curves for Raveling of Dense Graded Mixtures	209
Appendix Q: Simulated Probability Curves for Cracking of Open Graded Mixtures.....	220
Appendix R: Simulated Probability Curves for Rutting of Open Graded Mixtures.....	227
Appendix S: Simulated Probability Curves for Raveling of Open Graded Mixtures.....	234

LIST OF FIGURES

Figure 1. Illustration of Percent Within Limits (PWL) and Percent Defective (PD).	8
Figure 2. Illustration of Stepped and Continuous Payment Schedules (AASHTO, 2018).	10
Figure 3. Example of Multiple Straight lines Continuous Pay Factor (Hughes et al., 2011).	10
Figure 4. Example of an OC Curve for an Accept/Reject Acceptance Plan (AASHTO, 2018)...	13
Figure 5. Example of an OC Curve for an Acceptance Plan with Pay Adjustments (AASHTO, 2018).	13
Figure 6. Example of an EP Curve (AASHTO, 2018).	14
Figure 7. Hierarchy of FHWA Asphalt and Concrete Pavement PRS Tools.	18
Figure 8. Illustration of Performance-Modeling Procedure for Empirical PRS Method.....	19
Figure 9. Quality Measures (QMs) of Choice by SHAs.	24
Figure 10. Acceptance Quality Characteristics (AQC's) of Choice by SHAs.....	25
Figure 11. Location of Projects Identified for this Study.	31
Figure 12. Range of Composite Pay Factors for Dense Graded Mixes.	33
Figure 13. Range of Composite Pay Factors for Open Graded Mixes.	34
Figure 14. Distribution of Pay Factors for Dense Graded Mixtures.....	35
Figure 15. Distribution of Pay Factors for Open Graded Mixtures.	36
Figure 16. Distribution of Total Cracking for (a) Dense and (b) Open Graded Mixtures.....	38
Figure 17. Distribution of Rut Depth for (a) Dense and (b) Open Graded Mixtures.	39
Figure 18. Distribution of Raveling Index for (a) Dense and (b) Open Graded Mixtures.	39
Figure 19. Distribution of Pay Factors for Dense Graded Mixtures in the Comprehensive Database.....	41
Figure 20. Distribution of Pay Factors for Open Graded Mixtures in the Comprehensive Database.....	41
Figure 21. Example Cracking vs CPF Trend for Dense Graded Mixture (Project 209787-2).	43
Figure 22. Example Cracking vs CPF Trend for Open Graded Mixture (Project 406326-1).....	43
Figure 23. Network Level Cracking vs CPF Trend for Dense Graded Mixtures.	45
Figure 24. Network Level Cracking vs CPF Trend for Open Graded Mixtures.....	45
Figure 25. Network Level Cracking (Normalized by ADTT) vs CPF Trend for Dense Graded Mixtures.....	46
Figure 26. Network Level Cracking (Normalized by ADTT) vs CPF Trend for Open Graded Mixtures.	47
Figure 27. Network Level Cracking vs ADTT Trend for Dense Graded Mixtures.....	47
Figure 28. Network Level Cracking vs ADTT Trend for Open Graded Mixtures.	48
Figure 29. Probability of Cracking Category vs. CPF for Dense Graded Mixtures.	51
Figure 30. Logistic Regression Predicted Cracking Probability for Dense Graded Mixtures.....	52
Figure 31. Logistic Regression Predicted Cracking Probability for Open Graded Mixtures.	52
Figure 32. Logistic Regression Predicted Rutting Probability for Dense Graded Mixtures.	55
Figure 33. Logistic Regression Predicted Rutting Probability for Open Graded Mixtures.....	55
Figure 34. Logistic Regression Predicted Raveling Probability for Dense Graded Mixtures.....	57
Figure 35. Logistic Regression Predicted Raveling Probability for Open Graded Mixtures.	57
Figure 36. Summary of Logistic Regression Predicted Probabilities for Dense Graded Mixtures.	58
Figure 37. Summary of Logistic Regression Predicted Probabilities for Open Graded Mixtures.	59

Figure 38. Simulated Probability Curves for Dense Graded Mixture Cracking (Simulation ID 0 vs. 12).....	65
Figure 39. Simulated Probability Curves for Dense Graded Mixture Rutting (Simulation ID 0 vs. 12).	65
Figure 40. Simulated Probability Curves for Dense Graded Mixture Raveling (Simulation ID 0 vs. 12).....	66
Figure 41. Simulated Probability Curves for Open Graded Mixture Cracking (Simulation ID 0 vs. 7).....	67
Figure 42. Simulated Probability Curves for Open Graded Mixture Rutting (Simulation ID 0 vs. 7).	68
Figure 43. Simulated Probability Curves for Open Graded Mixture Raveling (Simulation ID 0 vs. 7).	68

LIST OF TABLES

Table 1. Common AQC's for Asphalt Concrete.....	5
Table 2. Specification Limits for Asphalt Concrete Recommended by AASHTO R 42-06.	7
Table 3. Examples of CPFs.....	11
Table 4. FDOT's HMA AQC's and Their Weights.	22
Table 5. FDOT's Specification Limits for HMA.....	22
Table 6. AQC's of Choice by SHAs Identified in Previous Studies.....	24
Table 7. GDOT's AQC's and Specification Limits for OGFCs.	26
Table 8. Maryland DOT's AQC's and Specification Limits for OGFCs and PEM.....	27
Table 9. Pay Factors in Maryland DOT Specification.....	27
Table 10. Mississippi DOT's AQC's and Specification Limits for OGFCs.....	28
Table 11. Mississippi DOT's AQC's and Specification Limits for OGFCs.....	28
Table 12. SCDOT's AQC's and Specification Limits for OGFCs.	29
Table 13. Pay Factor for Gradations in SCDOT Specification.....	29
Table 14. UDOT's AQC's and Specification Limits for OGSCs.	30
Table 15. Pay Adjustment for Gradations in UDOT Specification.	30
Table 16. Summary of p-values from Cracking Logistic Analysis (Dense Graded).....	50
Table 17. Summary of p-values from Cracking Logistic Analysis (Open Graded)	50
Table 18. Summary of p-values from Rutting Logistic Analysis (Dense Graded).....	53
Table 19. Summary of p-values from Rutting Logistic Analysis (Open Graded).....	53
Table 20. Summary of p-values from Raveling Logistic Analysis (Dense Graded)	56
Table 21. Summary of p-values from Raveling Logistic Analysis (Open Graded).....	56
Table 22. Weights of AQC's Simulated in Logistic Analysis (Dense Graded Mixtures)	63
Table 23. Weights of AQC's Simulated in Logistic Analysis (Open Graded)	64

1. INTRODUCTION

The Florida Department of Transportation (FDOT) has used a Quality Assurance (QA) specification based on random sampling and statistical concepts for acceptance and payment of hot mix asphalt (HMA) since 1977. According to FDOT's Standard Specifications for Road and Bridge Construction dated 2000, acceptance and payment of dense-graded HMA mixtures were determined based on asphalt binder content, gradation, and roadway density (FDOT, 2000). The payment was based on the average deviation from the target for asphalt binder content and gradation, while it was based on the percentage of maximum specific gravity (G_{mm}) for roadway density. The open-graded HMA mixtures were accepted based on asphalt binder content and gradation (FDOT, 2000).

Under the above QA specification, there were no provisions for the contractors to obtain an incentive (i.e., bonus), with the exception of roadway density for coarse-graded Superpave mixtures. However, the contractors could obtain a disincentive (i.e., reduction in pay) if the acceptance test results deviated too far from the target. In addition, although the contractors were required to perform quality control (QC) testing for process control purposes, these test results were not used for payment. For acceptance and payment, the contractors' HMA were evaluated based on random samples tested by FDOT's QA technicians.

The changes in the Code of Federal Regulations (CFR), or more specifically the 23 CFR 637 Part B: Quality Assurance Procedures for Construction, that took place in 1995 allowed the states to use Contractor's data for acceptance and payment, provided the following.

1. The sampling and testing have been performed by qualified laboratories and qualified sampling and testing personnel.
2. The quality of the material has been validated by the verification testing and sampling. The verification sampling shall be performed on samples that are taken independently of the quality control samples.
3. The quality control sampling and testing is evaluated by an Independent Assurance (IA) program.

With the above stipulation in the CFR, FDOT formed a task group composed of various experts from FDOT, contractors, Federal Highway Administration (FHWA), and consultants with the objective of developing a new specification that will allow the use of contractors' data for acceptance and payment. It was envisioned that such a specification would also reduce FDOT's QA testing requirements and staffing levels at the asphalt plant without sacrificing the quality of the HMA mixtures (Sholar et. al., 2003). FDOT also decided to utilize this opportunity to implement a Percent Within Limits (PWL) specification to replace the previous method based on average deviations.

1.1. BACKGROUND

Historically, state highway agencies (SHAs) have used various QA specifications for determining whether to accept or reject the product delivered by the contractors. Several quality

measures are available for use with these specifications. Similar to FDOT's experience, many SHAs have adopted the average deviation from a target value as the measure of quality in the 1960s and 1970s (Haider et. al., 2017). Over the years, SHAs realized that using the average deviation alone has limitations because it does not account for the variability of the construction material properties within a project. On the other extreme, variability alone as a quality measure can also be misleading as the entire project could have very low variability and high average deviation from the target value. As such, several quality measures that can incorporate both the average deviation and the variability of the quality characteristics have been recognized as better quality measures for QA specifications. Examples of such quality measures include Percent Defective (PD) and PWL.

FDOT's PWL specification for acceptance and payment of HMA materials was first implemented in 2002, as part of the Department's Contractor Quality Control (CQC) system. The CQC system uses contractors' verified QC data for acceptance and payment. Another major difference between FDOT's new PWL specification and the old specification, is that the PWL system allows the contractors to earn incentives or disincentives depending on the quality of their material and pavement constructed. Since the implementation of the PWL in 2002, the QA specification has been refined several times based on research and feedback from industry as well as from FHWA before arriving at the current specification.

1.2. RESEARCH OBJECTIVES

The basic premise of the incentive/disincentive specification based on the concept of PWL is that the long-term pavement performance is related to certain quality characteristics. However, such a relationship has not been defined or established based on FDOT's data. Due to the lack of such relationships, the quality characteristics and their weights currently implemented in FDOT's PWL specification were established empirically based on past experience and engineering judgement (Sholar et. al., 2003, 2005, and 2006). As such, one cannot ascertain if the PWL specification is cost-effective or if the quality characteristics and weights need to be updated. Consequently, the primary objective of this study is to determine the level of impact that incentive/disincentive specifications have on the long-term performance of asphalt pavements.

2. LITERATURE REVIEW

2.1. INTRODUCTION

High-quality pavement construction translates directly to robust performance and long life; the better the quality, the better the performance and the greater life of the finished pavement. Construction defects and consequences of poor construction practices affect the timeline, budget, and long-term performance of a completed project. By assessing the quality of produced materials and pavement construction practices before, during, and following construction, QA programs provide the owner agency and the contractor a means to achieve the desired long-term pavement performance. As such, the SHAs use established procedures and specifications to perform a wide range of material tests and as-built pavement evaluations during various stages of a construction contract in accordance with state-specific requirements and Code of Federal Regulations 23 CFR 637.207 (Code of Federal Regulations, 2020).

The cornerstone of a QA program is the time and effort that agencies and contractors put into following the best practices available for delivering quality products. As such, to achieve quality pavements, both contractor and inspector are responsible for ensuring that all construction activities are performed in close conformity with the plans and technical specifications. This requires a thorough understanding of the plans and specifications by all project parties, employing best construction practices, and close collaboration of project owner, inspector, and contractor for resolving any unexpected problems. However, many factors result in materials and construction variability, and therefore constructed pavement may not precisely achieve the quality required by design or by specification. This discrepancy between as-designed and as-constructed quality necessitates the development and implementation of QA specifications to address issues of testing (and test variability), sample size, lot size, estimates of the total population, percentage within limits, and pay adjustment factors.

2.2. QUALITY-BASED PAY ADJUSTMENT SYSTEM

In the 1960s, SHAs have started using QA specifications that involve a quality-related pay adjustment system for pavement construction acceptance and started paying contractors for the quality provided (Bowery and Hudson, 1976). A common pay adjustment system in QA specifications involves statistical sampling and testing programs that incorporate product variability into determination of payment. A more comprehensive approach, as promoted by performance-related specifications (PRS), uses predictive models along with statistical models to determine pay adjustments based on the difference between the as-designed and as-constructed life-cycle cost of the pavement.

When the constructed pavement quality is substantially deficient (i.e., significantly departs from the desired specifications), remove-and-replace or major remediation is generally required. Experience has revealed that when the delivered quality is marginally deficient, remove-and-replace should not be considered as the preferred action. To account for the value lost in substandard work, full payment is not warranted and therefore contractors are assessed disincentives, i.e., final payment is lower than the contract price. On the other hand, to motivate contractors and account for value gained by providing quality work that exceeds desired

specification requirements, many SHAs also offer incentives (bonus payments or pay increases). The key factors of an effective, implementable, and defensible quality-based pay adjustment system are listed below (Burati et al., 2003; Burati et al., 2004; Hughes et al., 2011).

- Acceptance Quality Characteristics (AQC)s
- Quality Measures (QMs)
- Pay Factors (or pay schedules)
- Composite Pay Factors (CPFs)
- Operating Characteristics (OCs) and Expected Pay (EP) Analyses

The following sections provide definitions and a brief description for the quality-based pay adjustment factors.

2.2.1. Acceptance Quality Characteristics (AQC)s

Acceptance Quality Characteristics (AQC)s are the foundation for the development of a quality-based pay adjustment system. According to the AASHTO R 10-06 entitled *Standard Practice for Definition of Terms Related to Quality and Statistics as Used in Highway Construction*, an AQC is “A quality characteristic that is measured and used to determine acceptability” (AASHTO, 2020). However, for development and implementation of a pay adjustment system, the AQC)s must be limited to those that are measured and used to determine pay factors (Burati et al., 2003; Hughes et al., 2011). Commonly-used AQC)s for pay adjustment systems are shown in Table 1. It is worth mentioning that there are many quality characteristics for asphalt mixture production (e.g., aggregate angularity) and in-place asphalt concrete (e.g., asphalt mat temperature) that are specified by agencies for acceptance but not necessarily used for payment scheduling.

The AASHTO R 42-06 entitled *Standard Practice for Developing a Quality Assurance Plan for Hot-Mix Asphalt (HMA)* states that “hot mix asphalt (HMA) properties used for acceptance typically include asphalt content (AC), air voids (AV), and voids in mineral aggregate (VMA), and other properties required by the agency” (AASHTO, 2020). The other requirements in this context frequently refer to one or more aggregate size, Voids Filled with Asphalt (VFA), mat density, thickness, ride quality, or joint density.

In general, the AQC)s can be divided into two main categories, Materials and Construction. The material AQC)s are measured from plant- or field-sampled asphalt mixtures, either loose or laboratory-compacted, while the construction AQC)s are measured from the compacted asphalt mat. As such, some SHAs developed pay adjustment systems that include two or more separate pay factors for material AQC)s and construction AQC)s. On the other hand, most SHAs combine material and construction AQC)s into a single composite pay factor. Common asphalt concrete AQC)s used in SHA acceptance plans and pay adjustment systems are summarized in Table 1.

Table 1. Common AQC's for Asphalt Concrete.

<p>Material AQC's</p>	<ul style="list-style-type: none"> • <i>Asphalt Content (AC)</i>: AC is one of the most frequently used AQC's by SHAs. The impact of AC on long-term asphalt pavement performance has been acknowledged for many years; the higher the AC, the higher cracking resistance and durability, but the lower rutting resistance. • <i>Air Voids (AV)</i>: Laboratory AV have been recognized as one of the most important indicators of pavement performance. Similar to AC, laboratory AV is also used by most SHAs. • <i>Voids in the mineral aggregate (VMA)</i>: Adequate VMA indicates sufficient room for asphalt binder which is critical for mixture durability and crack resistance. It is used as an AQC by several SHAs. • <i>Gradation</i>: One or more sieve sizes have been used as AQC's by many SHAs. However, to avoid too great a bias toward gradation, including too many sieves is not recommended. In addition, considering a fewer number of sieves gives the contractors the ability to control the gradation. As such, one sieve for the coarse portion of the gradation (e.g. percent passing the 12.5 mm sieve), one for the fine portion (e.g. percent passing the #4 or #8 sieves), and one for the fines (the percent passing the #200 (0.075-mm) sieve) would suffice. Several SHAs use one or more sieves as AQC's. • <i>Voids filled with asphalt (VFA)</i>: Inadequate VFA indicates less durable HMA resulting from a thin film of asphalt binder on the aggregate surface. VFA is used by a few SHAs for pay schedules.
<p>Construction AQC's</p>	<ul style="list-style-type: none"> • <i>Mat density</i>: Mat density is one of the most important AQC's for asphalt concrete acceptance and therefore it is used by most SHAs. Mat density is a predictor of long-term asphalt pavement performance and represents adequate AC and AV in the mixture. In other words, achieving desired mat density requires mixtures produced at the designed AC and AC. • <i>Thickness</i>: Pavement thickness is the main outcome of the pavement design process and can greatly impact long-term performance. Thickness is often used as an AQC. • <i>Ride quality</i>: To increase customer satisfaction, increased use of Ride Quality incentives has been initiated to encourage contractors to not only meet smoothness specifications but to exceed them. As such, ride quality has become a very important AQC. Ride quality, however, is mostly used as a separate AQC with a separate pay factor, meaning that it is not combined with other AQC's into a composite pay factor (Hanna, 2013; Merritt et al., 2015; Nair et al., 2018). • <i>Joint density</i>: Longitudinal joints can often be a critical source of premature failure in asphalt concrete pavements. Joint density has been recently identified as a useful AQC and is used by some SHAs either as a separate AQC or in a composite pay factor (Sebaaly et al., 2015; Zinke et al., 2008; Wang et al., 2016).

Even though AQC's vary appreciably among SHA specifications, they have been selected mostly based upon historical data and impact on final delivered quality and long-term pavement performance. The number of AQC's in a pay adjustment system may also depend on the project importance and size, material quantity, or project geometry. Using different sets of AQC's for different road function classifications (depending on traffic level) has been practiced by few SHAs. It was recommended that the use of interrelated AQC's (i.e., dependent AQC's) be avoided since they have a similar impact (a biased compound effect) on the pay factors (Hanna, 2013). However, agencies have used several interrelated AQC's (e.g., AC and AV) because of a general consensus on their impact on the asphalt concrete durability.

2.2.2. Quality Measures (QMs)

Quality Measures (QMs) refer to a mathematical parameter used for quantifying the level of quality of an individual AQC. Example QMs used by SHAs include average quality (i.e., mean), the variability (i.e., standard deviation), or a combination of both. While several QMs are available for use with the pay adjustment system, most common QMs are percent within limits (PWL), Percent Defective (PD), or Average Absolute Deviation (AAD) (Burati et al., 2003; Burati et al., 2004).

Historically, many SHAs adopted AAD, also referred to as average deviation from a target value, as the measure of quality in the 1960s and 1970s (Haider et. al., 2017). AAD only uses average as a population parameter related to quality. Over the years, SHAs realized that using the average deviation alone has limitations because it does not account for the variability of construction material property within a project. For example, low test values balance out high test values in a bimodal population, (i.e., two peaks with high variability), and the final AAD meets the specification (i.e., inconsistent project).

On the other extreme, variability alone as a quality measure can also be misleading as the entire project could have very low variability and high AAD value (i.e., consistently poor). As such, several QMs that incorporate both the average deviation from a target value and the variability of the AQC's have been recognized as better QMs for QA specifications. Examples of such quality measures include PWL and PD (FHWA, 2007). The PWL (or percent conforming) is preferred by most agencies over PD (or percent defective, i.e., nonconforming) because of its positive expression for the material outside of the specification limits that may not be strictly defective but rather be of lesser quality than material within the limits.

The PWL is the most commonly used and most effective QM that accounts for both central tendency (average) and population variability. Most SHAs as well as the Federal Highway Administration (FHWA) and the Federal Aviation Administration (FAA) use PWL in their specifications (Hughes et al., 2011). In addition, the AASHTO R 9-05 entitled *Standard Practice for Acceptance Sampling Plans for Highway Construction* and the AASHTO R 42-06 emphasize the importance of PWL as part of an acceptance plan (AASHTO, 2018; AASHTO, 2020). As implied by its name, the PWL statistic is simply the statistical estimate of the amount (or proportion) of a material or construction AQC that is within certain specification limits. The specification limits are the limiting values placed on an AQC for evaluating the conformity of delivered material or construction with the requirement specified by the agency specification.

As such, an AQC and its associated specification limits are expressed in the same units. If the specification limits include either an individual upper specification limit (USL) or lower specification limit (LSL), it is called “single specification limit”. If both USL and LSL are specified, it is referred to as “double specification limits” (Transportation Research Circular E-C235, 2018). Table 2 shows the specification limits for asphalt concrete recommended by AASHTO R 42-06 (AASHTO, 2020).

Table 2. Specification Limits for Asphalt Concrete Recommended by AASHTO R 42-06.

AQCs	Specification Limits
AC (%)	Extraction: ±0.41
	Nuclear gage: ±0.30
	Ignition furnace: ±0.21
AV (%)	±1.60
VMA (%)	±1.60
VFA (%)	±8.0
Mat density	±2.3

The concept of the PWL approach is illustrated in Figure 1 for double specification limits (i.e., with USL and LSL). The PWL approach assumes that material and construction properties follow a normal distribution. Conceptually, the PWL procedure is similar to determining areas under the normal distribution that can be calculated to determine the percentage of the population that is within certain limits by using the standard normal variant, Z . However, instead of using the Z -value and the standard normal curve, the PWL is estimated by using the quality index, Q . The PWL statistic of an AQC is calculated from the upper and lower quality indices (i.e., Q_U and Q_L , respectively) defined as the following.

$$Q_U = \frac{USL - \bar{X}}{s} \quad (1)$$

$$Q_L = \frac{\bar{X} - LSL}{s} \quad (2)$$

where,

- Q_U = Upper quality index
- Q_L = Lower quality index
- s = Sample standard deviation for a given LOT

The above quality indices are used to find the percentage of material below the USL (i.e., P_U) and above the LSL (i.e., P_L), typically from tables (e.g., Table 334-10 in FDOT’s July 2022 Specification) or through other statistical routines (Burati et al., 2003; Haider et. al., 2017; Coenen, 2019). The PWL statistic is then obtained from P_U and P_L values as the following.

$$PWL = (P_U + P_L) - 100 \quad (3)$$

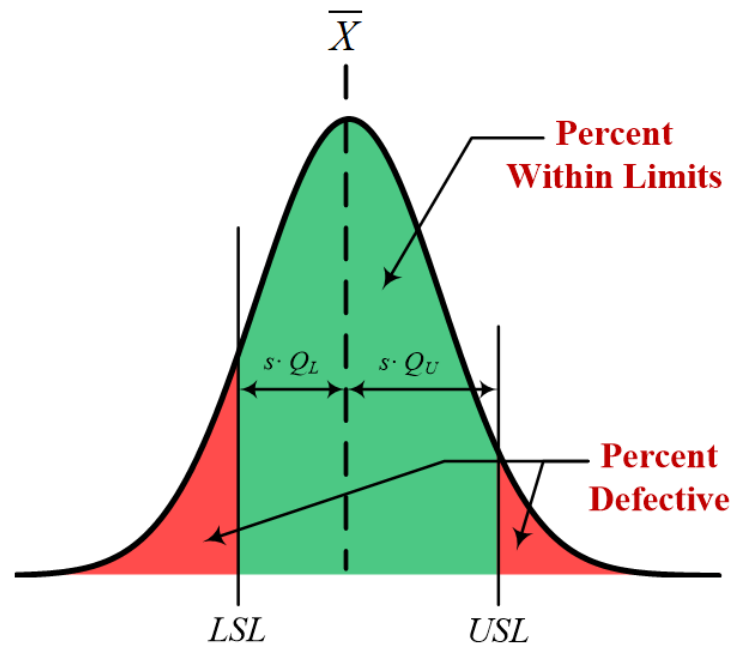


Figure 1. Illustration of Percent Within Limits (PWL) and Percent Defective (PD).

In addition, in the development of an acceptance plan and a pay adjustment system using a PWL or PD approach, agencies must also specify the acceptance limits, namely the acceptable quality level (AQL) and rejectable quality level (RQL). AQL is defined as the minimum level of quality at which the material or construction can be considered fully acceptable for the AQC of concern. On the other hand, RQL is the maximum level of quality outside of which the material or construction can be considered unacceptable or rejectable (Transportation Research Circular E-C235, 2018). As suggested in the AASHTO Quality Assurance Guide Specification, the AQL is usually set to be 90 PWL (AASHTO, 1995).

Specification limits and acceptance limits are frequently determined based on engineering requirements and are established using a target value for an AQC and typical standard deviation. With a specified AQL (say 90 PWL), the specification limits need to be set such that the population with an average at the target value and a certain standard deviation has 90 percent of its area within the specification limits. Therefore, specification limits are determined as $\pm Z$ standard deviations from the target value (i.e., $\mu \pm Z\sigma$) where the Z -score can be found from a standard normal table corresponding to the area represented by the AQL (e.g., $Z = 1.645$ for 90 PWL).

Since the specification limits and AQL are interrelated, the engineering decisions regarding these values are typically made concurrently. For instance, the AQL might be set at 90 PWL, meaning that when 90 percent of the product (i.e., material AQC or construction AQC) is within specification limits, the product is completely acceptable. However, the same product could be defined acceptable at an AQL of 85 PWL with more restrictive specification limits. In other words, many possible combinations of AQL and specification limits can be used to define an acceptable or rejectable product. However, selecting lower values of AQL may give the

perception that lower quality levels are acceptable. As such, it is recommended AQL values be set to 90 or 95 PWL (AASHTO, 2018).

It should be noted that an acceptance plan and a pay adjustment system should be designed in such a way that a material or construction AQC meeting the AQL receives an expected pay (EP) of 100 percent. In addition, the RQL must be defined and used along with the AQL to account for risks associated with deficient material or construction (i.e., significant departure from the desired specifications). The common practice for RQL is to either have a minimum pay factor, require the contractor to remove-and-replace the asphalt concrete, or do major remediation (AASHTO, 2018).

2.2.3. Pay Factor

Pay factor (PF) or pay schedule is one of the most important items of an acceptance plan. From a quality-based pay adjustment system perspective, the quality and performance must be related to the pay factor. Pay factors are expressed either in continuous (equation-type) form or stepped tabular form. According to the AASHTO R 9-05 recommendation, the following two conditions apply to any pay schedule (AASHTO, 2018):

1. The pay factor for an individual LOT should be 1.00 when its PWL is equal to the AQL.
2. For multiple LOTs, the average pay factor should be 1.00 when the average PWL is equal to the AQL. Clearly, this indicates that there must be an incentive when the PWL is above the AQL to compensate for the disincentive resulting from PWL below the AQL.

The most commonly used and well-accepted continuous pay factor is the AASHTO equation expressed in the following equation (AASHTO Quality Assurance Guide Specification, 1995). It can be seen that at 100 PWL, the maximum pay factor is 1.05, while at the AQL of 90 PWL, the pay factor is 1.00.

$$PF = (55 + 0.5 \times PWL) / 100 \quad (4)$$

It should be noted that the relationship between quality, as measured by PWL, and value, as determined by pay factor, may not be necessarily linear as indicated by the equation above. As such, another approach is to relate the pay factor equation to performance that can be in a stepped tabular form or in a continuous (but necessarily linear) form.

An example of a stepped tabular form of pay factor is shown in Figure 2 (AASHTO, 2018). As shown in this figure, a continuous pay factor smoothly progresses as the PWL varies. However, for the stepped tabular pay factor, when the PWL is close to the boundary of the steps, a small change in the calculated PWL can result in a substantial difference in the payment. Accordingly, continuous (equation-type) pay factors are more straightforward that avoid disputes in such circumstances over measurement precision. As such, if an agency decides to use a stepped tabular pay factor, it is necessary to use a series of many relatively small steps (AASHTO, 2018).

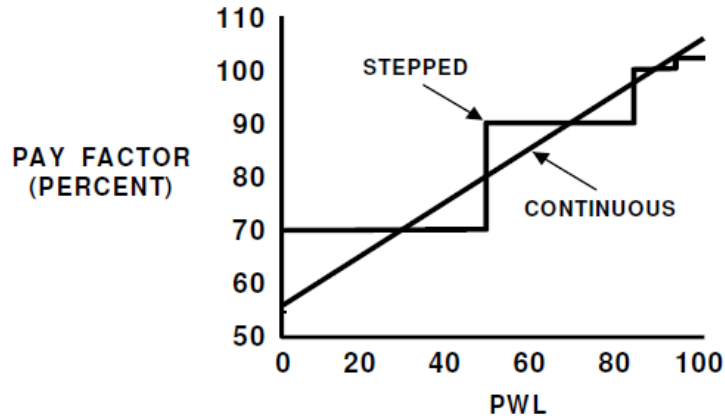


Figure 2. Illustration of Stepped and Continuous Payment Schedules (AASHTO, 2018).

There are other forms of continuous (equation-type) pay factors composed of multiple linear (similar to the AASHTO equation but with different slope and intercept) or nonlinear pay factors. Figure 3 illustrates an example of a continuous pay factor composed of multiple straight lines. An example of nonlinear pay factor which is developed and used by the Virginia Department of Transportation (VDOT) for HMA (Hughes, 1995) is expressed in Equation (5). The purpose of using different pay factor equations is to better relate the quality to payment by accentuating the incentive or the disincentive.

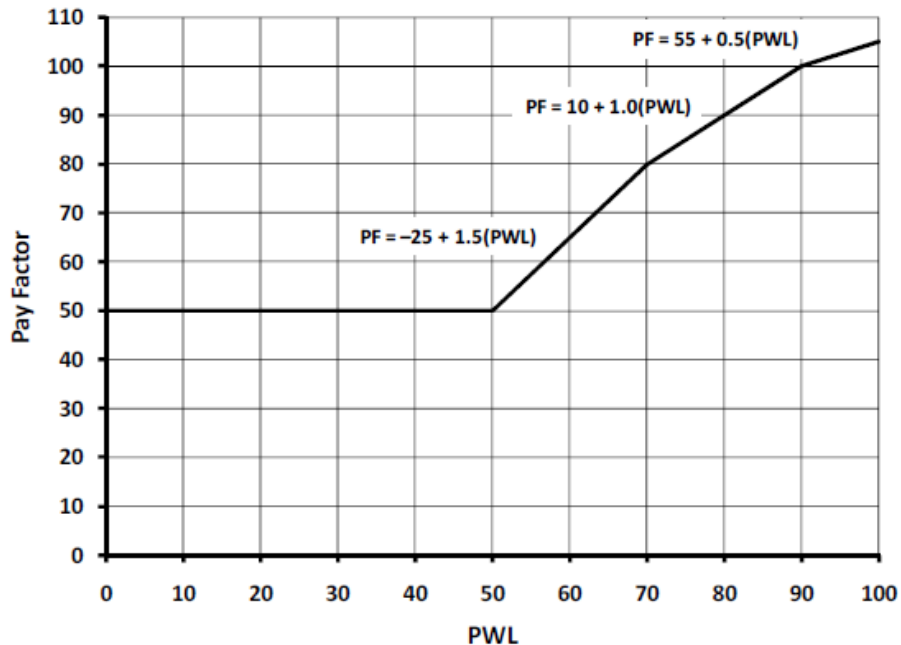


Figure 3. Example of Multiple Straight lines Continuous Pay Factor (Hughes et al., 2011).

$$PF = -0.01166(PWL)^2 + 2.2039(PWL) - 3.716 \quad (5)$$

2.2.4. Composite Pay Factor (CPF)

Most acceptance plans and pay adjustment systems include multiple AQC's and therefore, involve multiple pay factors. A composite pay factor (CPF) is a model that combines multiple pay factors by assigning weights to different pay factors. There are several ways of developing composite pay factors including the minimum, average, multiplication, or weighting system. However, most SHAs utilize a weighting system to combine individual pay factors based on the concept that some AQC's are more important (i.e., higher weight) than the others (Hanna, 2013). The general form of a weighted pay factor equation is given in the following.

$$CPF = \sum_i \frac{W_i \cdot PF_i}{100} \quad (6)$$

Where PF_i and W_i are the pay factors and weights of each (i.e., i^{th}) AQC. As the CPF is simply a weighted average of the individual PF values, it shares the same range as the individual PF values.

In a weighting system, experience-based or statistically-determined weights with different magnitude are used to account for the impact of individual AQC on quality. In addition, most agencies combine both material and construction AQC's into a single CPF. There are some agencies, however, that use two or more CPF's separately for material AQC's and construction AQC's. Examples of material CPF, construction CPF, and material and construction CPF are presented in Table 3. The coefficients (or weights) in these equations are chosen considering the importance of each AQC using AASHTO R 42-06, AASHTO R 9-05, and other agencies' practice (Hughes et al., 2011).

Table 3. Examples of CPFs.

Material CPF	$CPF = 0.40(PF_{AC}) + 0.40(PF_{AV}) + 0.10(PF_{VMA}) + 0.03(PF_{\#4\text{or}\#8\text{sieve}}) + 0.07(PF_{\#200\text{sieve}})$
Construction AQC's	$CPF = 0.40(PF_{Den}) + 0.2(PF_{Thick}) + 0.4(PF_{RQ})$
Material and Construction CPF	$CPF = 0.20(PF_{AC}) + 0.35(PF_{AV}) + 0.10(PF_{VMA}) + 0.35(PF_{Den})$ $CPF = 0.15(PF_{AC}) + 0.15(PF_{AV}) + 0.10(PF_{Thick}) + 0.30(PF_{Den}) + 0.30(PF_{RQ})$

Using more AQC's than needed to define quality and determine CPF is an obstacle for implementation of the pay adjustment system. In addition, there are risks associated with composite pay factors (to be discussed subsequently), and therefore including unnecessary AQC's makes the calculation of risks more complicated (AASHTO, 2018). As noted earlier, using AQC's that are highly interrelated should be avoided. If AQC's are interrelated, the joint effect should be minimized by using smaller weights for their associated individual pay factors. While there is no specific guideline or procedure for selecting the number of AQC's for a pay

adjustment system, it is well-accepted that only those AQC's that are predictors of quality and long-term pavement performance should be used.

2.2.5. Operating Characteristic (OC) and Expected Pay (EP) Analyses

The probability of making a wrong decision and therefore assigning a wrong pay adjustment to a finished product is considered as risk. Risk evaluation is a necessary step in the development and implementation of a pay adjustment system. There are two types of risks: (1) seller's or contractor's risk (α) or Type I error; and (2) buyer's or agency's risk (β) or Type II error (Transportation Research Circular E-C235, 2018).

Contractor's risk is the probability that an acceptance plan will erroneously reject AQL material and construction. It is the risk the contractor bears due to rejection of AQL material and construction. On the other hand, agency's risk is the probability that an acceptance plan will erroneously accept deficient material and construction. In general, the goal of an acceptance plan and pay adjustment system is to minimize and balance the risks between the agency and the contractors by minimizing the likelihood of AQL material and construction being rejected or deficient material and construction being accepted.

The operating characteristic (OC) and expected pay (EP) curves are valuable tools recommended by AASHTO R 9-05 for assessing risk (AASHTO, 2018). In order to calculate and generate OC and EP curves over a wide range of AQC quality levels, Monte Carlo simulations using historical AQC data (average and standard deviation) are usually performed. Monte Carlo simulation is a probabilistic approach that facilitates risk assessment and evaluates the expected behavior of various acceptance plans and pay schedules. A newly developed computer program, "SpecRisk", can perform the required risk analyses and Monte Carlo simulations. Note that the FHWA did not formally release "SpecRisk" for public use. The software is in the process of being made to be more user-friendly, and thus only the New Jersey Department of Transportation (NJDOT) and a small number of other organizations have been permitted to use it (Wang et al., 2015).

An OC curve is defined as "a graphic representation of an acceptance plan that shows the relationship between the actual quality of a lot and either (1) the probability of its acceptance (for accept/reject acceptance plans) or (2) the probability of its acceptance at various pay levels (for acceptance plans that include pay adjustment provisions)" (Transportation Research Circular E-C235, 2018). Figure 4 shows an example OC curve generated by SpecRisk for an accept/reject acceptance plan, along with the agency's risk and contractor's risk (AASHTO, 2018). As shown in Figure 4, for the range of quality levels indicated on the horizontal axis, the probability of acceptance can be determined on the vertical axis.

Figure 5 shows another example in which multiple curves, one for each of several selected pay factor levels. Each curve plotted in this figure represents the probability of receiving a pay factor equal to or greater than the one indicated for the line. For example, for the PWL exactly at AQL, there is a 45 percent chance of receiving a pay factor of 1.04 (PF = 104 percent) or greater, and a 60 percent chance of receiving full pay (PF = 100 percent) or greater (this also translates to a 40 percent chance of receiving less than 100 percent pay). On the other hand, the RQL product (i.e., product that is at exactly RQL) has approximately a 50 percent chance of receiving a pay factor

of 0.80 (PF = 80 percent) or greater. Similar interpretations can be determined for any level of quality and pay factor levels.

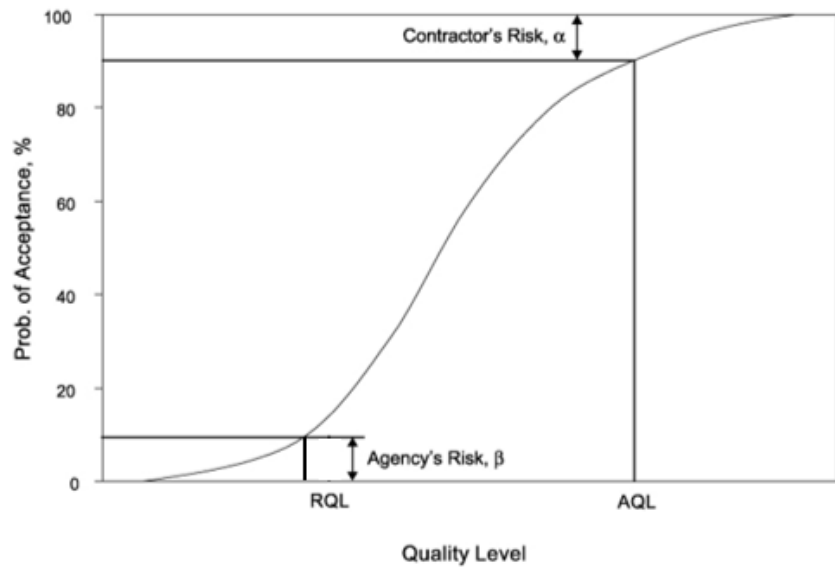


Figure 4. Example of an OC Curve for an Accept/Reject Acceptance Plan (AASHTO, 2018).

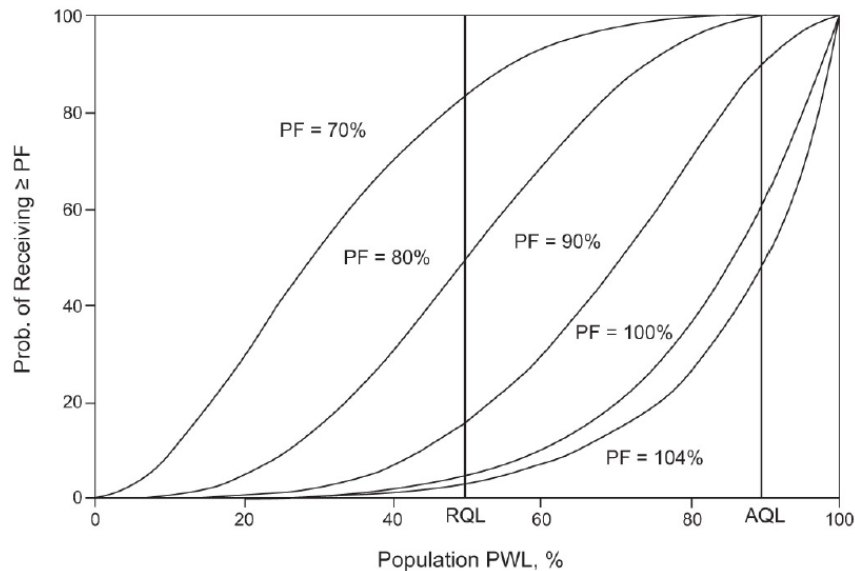


Figure 5. Example of an OC Curve for an Acceptance Plan with Pay Adjustments (AASHTO, 2018).

While OC curves provide information to evaluate risk, and the likelihood of receiving any specific pay factor (or higher), using multiple OC curves is confusing and it is not the best way to evaluate the pay adjustment system with respect to the long-term average payment for any given quality level. Thus, EP curves that are easier to interpret and understand, are frequently used as alternatives. An EP curve is defined as “a graphic representation of an acceptance plan that shows the relation between the actual quality of a lot and its EP, i.e., mathematical pay

expectation, or the average pay the contractor can expect to receive over the long run for submitted lots of a given quality” (Transportation Research Circular E-C235, 2018). An example of an EP curve is shown in Figure 6. The vertical axis, instead of probability of acceptance, gives the expected (long-term average) pay factor as a percent of the contract price. It should be noticed that both OC and EP curves should be used concurrently to evaluate how well a pay adjustment system and acceptance plan is theoretically expected to work.

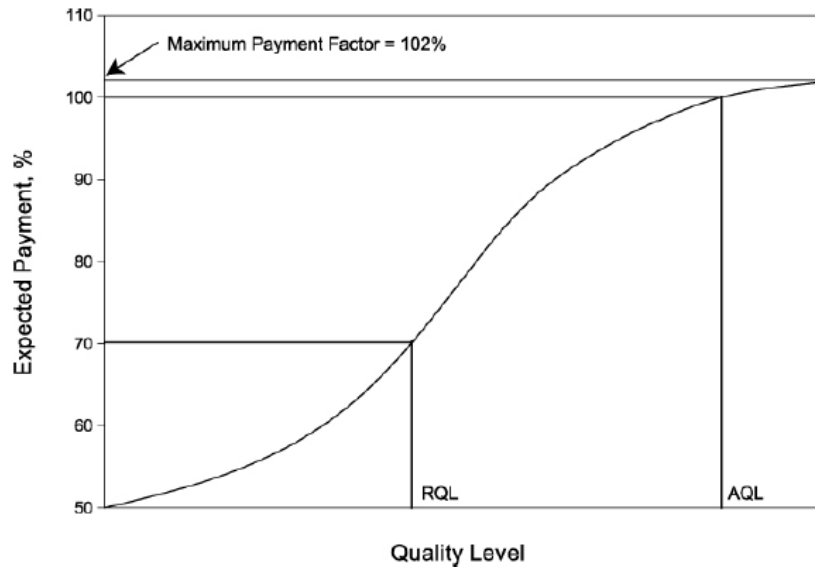


Figure 6. Example of an EP Curve (AASHTO, 2018).

2.3. PERFORMANCE-RELATED SPECIFICATIONS (PRS)

The QA specifications currently used by SHAs do not necessarily take the long-term performance into consideration in the sense that they have been developed based on the quality factors (i.e., AQC, quality measures, specification limits, AQL, and RQL, and pay factors) that are not directly tied to the performance of the asphalt mixture or the in-place pavement. To address such limitations, the focus in the recent decades has been given to the development of comprehensive QA specifications, referred to Performance-Related Specification (PRS), which is capable of relating the quality factors to long-term performance (McCarthy et al., 2016).

PRS is a step along the QA continuum toward performance-based acceptance. PRS is defined as a QA specification that describes the desired levels of key materials and construction AQC that have been found to correlate with fundamental engineering properties that predict performance (Transportation Research Circular E-C235, 2018). This definition clearly indicates that the selected AQC must be directly related to performance through field validated empirical or mechanistic prediction models. These performance prediction models account for the effect of deviations of the as-built AQC level from the associated as-designed level. As such, a true PRS not only describes the importance of the selected AQC on long-term performance but also employs quantified relationships to predict pavement performance using the selected AQC. Thus, they provide the basis for rational acceptance and pay adjustment decisions.

A significant amount of effort has been made over the past decades to develop mechanistic models for use in PRS. One of the first major attempts to develop PRS for asphalt concrete was the WesTrack project entitled *Accelerated Field Test of Performance-Related Specifications for Hot-Mix Asphalt Construction* (Epps et al. 2002). The WesTrack is a 1.8-mile oval-shaped road composed of 34 experimental asphalt pavement sections. Triple-trailers were used for accelerated testing to measure pavement performance. The two primary objectives of this project were: (1) to provide data to support the continued development of PRS for asphalt concrete by examining the influence of deviations in materials and construction properties affect long-term pavement performance; and (2) to provide field verification of the Superpave mix design procedures developed through the original Strategic Highway Research Program (SHRP) Asphalt Research Program. The measured performance characteristics, cracking and rut depth, were used to develop performance models in conjunction with the AQC's (aggregate gradation, binder content, and air voids). The results were used to develop simple empirical relationships for performance prediction to support PRS.

Development of a comprehensive PRS requires a significant amount of work including the selection of desired performance criteria; establishment of the relationships between material and construction AQC's and pavement response and performance; and defining the material characterization methods. In addition, other factors such as environment, traffic, pavement cross section, and variability (materials and construction) must also be considered in a comprehensive PRS. Thus, as reported in the NCHRP Project 20-05, Topic 46-03 entitled *Performance Specifications for Asphalt Mixtures*, PRS has seen only limited use to date (McCarthy et al., 2016). In this study, the results of the survey responses submitted by more than 55 U.S. States and Canadian provincial highway agencies identified several challenges of moving towards PRS for acceptance of asphalt mixtures, including lack of information on implementation strategies, cost of performance testing equipment, lack of training, and lack of familiarity in the asphalt paving industry, etc. The study concluded that future enhancements, such as the development and incorporation of more simple and reliable test methods, performance prediction models, and implementation guidelines that are consistent with the work being performed to advance performance-based mixture designs and mechanistic-empirical pavement structural design can make agencies and industries more interested in a wider application of PRS.

2.4. DEVELOPMENT OF QUALITY-BASED PAY ADJUSTMENT SYSTEM

A variety of acceptance plans and pay adjustment systems, containing different AQC's and using various statistical measures, have been developed and are used by SHAs. The primary goal of a pay adjustment system is to truly relate quality and pavement performance to the payment (i.e., quality-based pay adjustment system). There are several important considerations that must be addressed during the development of a quality-based pay adjustment system, including the following (Hughes et al., 2011).

- Select AQC's that are truly related to the long-term performance of the finished product.
- Determine specification limits, AQLs and RQLs, for AQC's that will result in the desired performance.
- Investigate the availability of reliable sampling and testing methods to accurately measure the quality.

- Evaluate the capability of the contractors to achieve the desired acceptance requirements without imposing extraordinary risks and using quality checks.
- Develop fair pay schedules that account for expected gains or losses through incentives and disincentives.

SHAs have to ensure that the pay relationships are defensible, effective, as well as, fair, and equitable to all parties. Methods aiming to develop rational quality-based pay adjustment systems have been investigated for many years (Willenbrock et al., 1977; Afferton et al. 1995; Hughes et al., 2011). These methods can be categorized into (a) engineering-based methods, (b) empirical-based methods, and (c) experience-based methods.

2.4.1. Engineering-based Methods

The engineering-based methods, which are also referred to as Complex Methods, have been developed based upon engineering principles and mathematical models that use computer software to perform the analyses. These methods identify the appropriate AQC and their relationship to long-term performance utilizing mechanistic or empirical pavement performance prediction models along with cost-evaluation procedures such as Life Cycle Cost Analysis (LCCA). Thus, these methods conform to the definitions of PRS described in AASHTO R 10-06 that require AQC to be correlated to fundamental engineering properties that predict pavement performance (AASHTO, 2020). The HMA Spec software, Quality-Related Specification Software (QRSS), and PASSPave™ are examples of these methods for asphalt pavement.

As previously noted, one of the original research projects related to the development of a PRS for asphalt mixtures was conducted at the WesTrack site. The HMA Spec software is the product of the WesTrack project and its continuation under the NCHTP Project 9-20 entitled *Performance-Related Specifications for Hot-Mix Asphalt Construction* (Epps et al. 2002). To develop the HMA Spec PRS-based software, the volumetric properties of the as-built asphalt concrete were utilized to develop simple empirical relationships for performance prediction. This software requires about 100 user inputs to perform the analyses. It has been reported that this software requires a thorough beta testing to determine programming errors and needs to be robust and user-friendly to ease implementation. The HMA Spec software is not available for public distribution and it has been superseded by a PRS developed from the Mechanistic-Empirical Pavement Design Guide (MEPDG) software in the NCHRP Project 9-22 entitled *Beta Testing and Validation of HMA PRS* (Moulthrop and Witczak, 2011).

The NCHRP Project 9-22 was conducted to refine PRS models that led to the development of the Quality-Related Specification Software (QRSS). The QRSS uses a database of pre-solved solutions of the MEPDG for predicting rutting, fatigue cracking, low-temperature (thermal) cracking, and pavement smoothness in terms of International Roughness Index (IRI) of asphalt pavement using the mix volumetric and binder and aggregate properties (Moulthrop and Witczak, 2011; Moulthrop et al., 2012). The QRSS determine Predicted Life Difference (PLD) by comparing the as-built pavement performance, using the contractor's lot or sub-lot quality assurance data, with that of the as-designed pavement, using the job mix formula. The calculated differences determine pay factors for each LOT or sub-lot. In addition, the performance predictions are project-specific meaning that the QRSS accounts for the climate, traffic,

pavement structure, and desired or expected service life. Further, the predictions are probabilistic and they are calculated through a Monte Carlo procedure that uses historical standard deviations of the input properties in order to account for construction and testing variabilities when assigning risk between the owner agency and the contractor.

In the 2000's, FHWA identified the implementation of performance specifications for asphalt mixtures as a high priority. An FHWA research is underway for developing and refining PRS for asphalt pavements that include rutting, fatigue cracking, and aging based on Linear Viscoelastic Continuum Damage (LVECD) modeling and establishing the predictive relationships between mixture volumetrics and performance characteristics, the Performance Volumetric Relationships (PVR). A significant effort under this contract is the development of the PASSFlex™, FlexPAVE™, FlexMIX™, and FlexMAT™ software and incorporation into PASSPave™. The PRS specification has evolved and now consists mainly of two components: mixture performance testing using the Asphalt Mixture Performance Tester (AMPT) analyzed using FlexMAT™, and pavement performance prediction using FlexPAVE™. The AMPT performance testing matrix includes the Dynamic Modulus, Direct Tension Cyclic Fatigue, and Simplified Triaxial Stress Sweep tests. For data analysis, test results are input into FlexPAVE™, a three-dimensional finite element program, to predict pavement distresses as a function of age, taking into consideration pavement structure, traffic, and climate conditions. The predicted pavement distresses are then used in PASSFlex™ to determine pay factors by comparing the as-built versus as-designed pavement lives. As of September 2016, a number of shadow PRS projects have been completed through collaboration with several state highway agencies (i.e., Maine, Missouri, North Carolina) and the Western Federal Lands (Duval, 2016). Figure 7 shows a hierarchy of asphalt and concrete pavement PRS tools.

Although the engineering-based methods (i.e., HMA Spec, QRSS, and PASSPave™) are capable of supporting the development of an accurate and reliable quality-based pay adjustment system, they require a large number of inputs and the errors associated with these inputs adversely affect the accuracy of the developed pay adjustment system, and therefore make their implementation complicated. For these reasons, none of these methods were considered a potential candidate for enhancement and adoption as a recommended practice in NCHRP Project 10-79 entitled *Guidelines for Quality-Related Pay Adjustment Factors for Pavements* (Hughes et al., 2011).

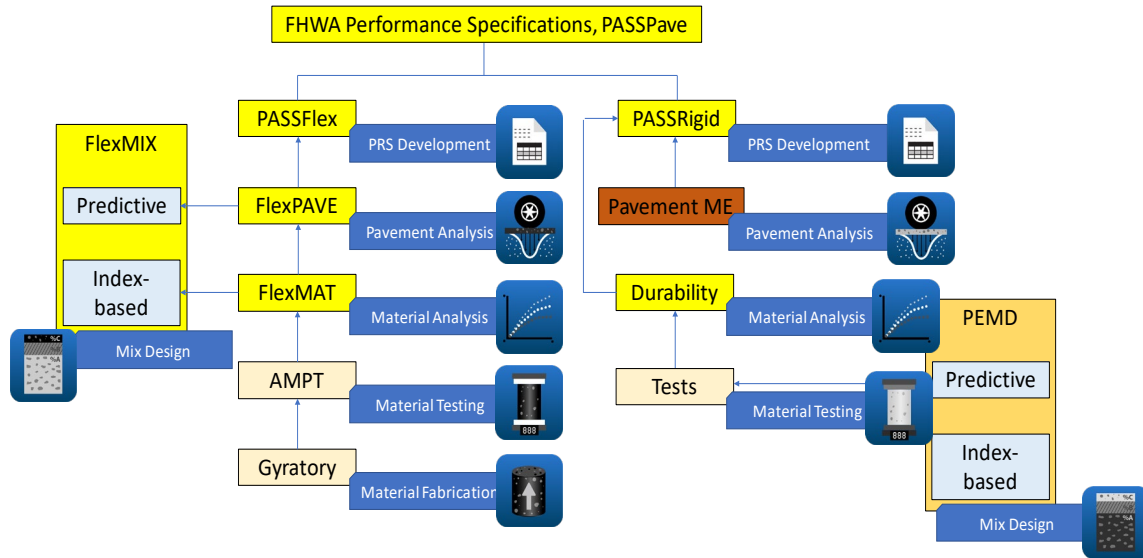


Figure 7. Hierarchy of FHWA Asphalt and Concrete Pavement PRS Tools.

2.4.2. Empirical-based Methods

Similar to the engineering-based method, the empirical-based methods also employ engineering principles and mathematical models, whereas the latter relies on empirical data and SHAs' experience to relate the pay adjustment system to quality and performance. Although these methods are likely to be less precise than the engineering-based methods, they are straightforward and understandable and that eases their adoption by SHAs. Furthermore, they use a performance-related concept, which promotes high-quality construction and more widespread adoption of PRS.

An example of an empirical-based method is the empirical PRS method which has been referred to as the expected life method. This is defined as a procedure to develop performance-related highway construction specifications by first developing mathematical models based on empirical performance data, and then applying life-cycle-cost analysis to establish pay adjustment provisions related to predicted performance (Transportation Research Circular E-C235, 2018). This method, which has been successfully employed by the NJDOT (Weed, 1999; Weed, 2003; Weed, 2006), includes two basic mathematical models: (a) a performance model defining the expected life as a function of delivered quality, and (b) an economic model expressing gained or lost value as a function of expected life. To develop and implement an empirical PRS method, acceptance data and calculated level of quality received (PWL or PD) are used to estimate the expected service life using the established performance equation. This result is then entered into a life-cycle-cost model to determine the incentive or disincentive and the final payment. Figure 8 depicts the performance modeling procedure.

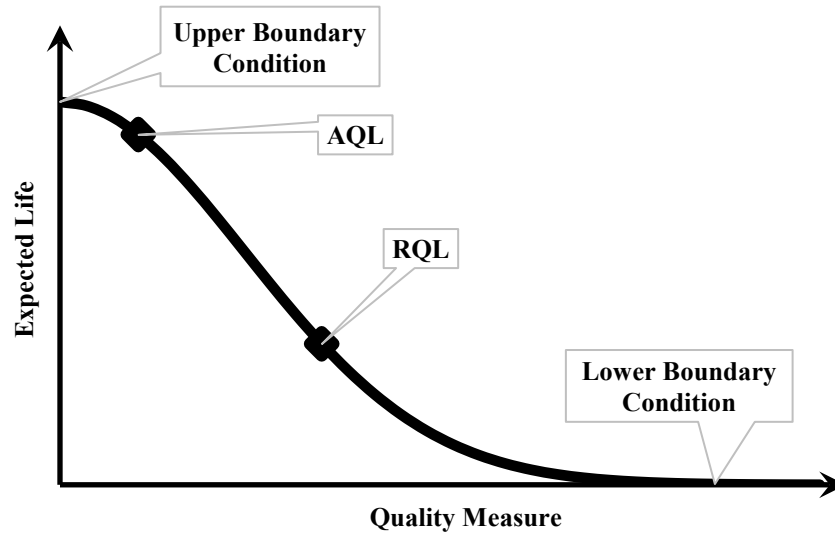


Figure 8. Illustration of Performance-Modeling Procedure for Empirical PRS Method.

2.4.2.1. Development of Performance Model

In order to develop the performance model, the following steps should be exercised:

- *Select statistical quality measure (QM):* Previous studies have concluded that percent within limits (PWL) and percent defective (PD), which are different representations of quality (i.e., $PD = 100 - PWL$), have been preferred in recent years because they simultaneously measure both the average level and the variability in a statistically efficient way (Burati et al., 2003; Hand and Epps, 2006). As described below, PD is the statistical quality measure of choice because it is a simpler mathematical form for the derivation process.
- *Select an appropriate mathematical form for the performance model:* As illustrated in Figure 8, it is well accepted that the mathematical shape of expected service life (i.e., performance data) as a function of the delivered quality of AQC's (i.e., PD) has points of diminishing returns which means that a model with an S shape may be appropriate (Weed, 1999; Weed, 2006). The exponential function expressed in Equation 7 is capable of producing an S-shaped function that accounts for multiple AQC's.

$$EXPLIF = e^{(B_0 + \sum B_i PD_i^C)} \quad (7)$$

where,

- $EXPLIF$ = Expected service life
- PD = Percent defective
- B_0, B_i = Coefficients
- C = Shape factor, a common exponent for all PD terms
- i = identifier of individual quality characteristics

- *Set up a general performance matrix:* In order to determine the coefficients (i.e., B_i and C) of the performance model, a set of simultaneous equations must be developed. To do so, the first necessary step is to establish a performance matrix. Equation 8 shows a generic matrix that needs to be completed to apply to this method. In the first row of the performance matrix, all AQLs are at their respective AQL values, thus the expected life is equal to the design life. For the remainder of the rows in the matrix, one AQL is set at some specified poor level of quality (preferably at the RQL), while all the others remain at the AQL. This provides the most convenient arrangement of performance data that can be set up relatively easily. The values to be entered into the matrix might be developed as the collective opinion of experienced pavement engineers, or they might be obtained more formally through a multiple-regression analysis of actual field data. In some cases, the agency's current pavement design method may be able to provide some of this information.

$$\begin{pmatrix} AQL_1 & AQL_2 & AQL_3 & \cdots & AQL_k & EXPLIF_1 \\ RQL_1 & AQL_2 & AQL_3 & \cdots & AQL_k & EXPLIF_2 \\ AQL_1 & RQL_2 & AQL_3 & \cdots & AQL_k & EXPLIF_3 \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ AQL_1 & AQL_2 & AQL_3 & \cdots & RQL_k & EXPLIF_k \end{pmatrix} \quad (8)$$

2.4.2.2. Development of Economic Model

The next step in the development of an empirical PRS method is to determine the economic impact of the estimated expected life. The frequently accepted way to establish the link between the delivered quality and gained or lost value is through the use of LCCA. A valid LCCA cost model needs to precisely take the construction and maintenance practices into consideration. The development of the economic model is based on the fact that there is a cost associated with the need to make corrections for defective work. Similarly, there is also a corresponding benefit associated with delaying future expenses by providing superior work. This development justifies both aspects of incentive and disincentive pay schedules. The basic economic model is expressed in Equation 9.

$$PAYADJ = PC \frac{(R^{DESLIF} - R^{EXPLIF})}{(1 - R^{OVLIF})} \quad (9)$$

$$R = \frac{(1 + INF)}{(1 + INT)} \quad (10)$$

where,

- $PAYADJ$ = Pay adjustment
- PC = Present total cost of overlay or resurfacing
- $DESLIF$ = Asphalt concrete design life
- $EXPLIF$ = Predicted expected life from the performance model

- OVLIF* = Expected life of successive overlay or resurfacing (typically 10-years)
- INF* = Long-term annual inflation rate
- INT* = Long-term annual interest rate

2.4.3. Experience-based Methods

The experience-based methods usually are not based upon either engineering principles or mathematical models. These methods do not provide pavement performance prediction, but they compute pay factors based on considering the relation of AQC's to pavement performance. This general approach has been in use for several years and appears to be functioning well and effective for SHAs (Hanna, 2013). These methods follow AASHTO R 9-05 and AASHTO R 42-06 (AASHTO, 2018; AASHTO, 2020).

2.5. OVERVIEW OF FDOT'S INCENTIVE/DISINCENTIVE SPECIFICATION

As mentioned previously, FDOT's PWL specification for acceptance and payment of HMA was first implemented in 2002. For open- and dense-graded HMA mixtures, four and five material properties believed to be most crucial for mixture performance were selected as AQC's, respectively. The weights corresponding to these quality characteristics were established according to their respective contribution to the overall quality of the pavement, which was also determined based on engineering judgment. Table 4 summarizes the quality characteristics and their weights that are currently implemented in FDOT's most recent PWL specification. Table 5 summarizes FDOT's most recent specification limits (FDOT, 2020). In addition, FDOT's PWL specification uses the AASHTO equation to determine PF. It states that the contractor should remove and replace any LOTs with *CPF* less than 0.75. As such, most of FDOT's *CPF* values range from 0.75 to 1.05.

For the purpose of testing, acceptance, and payment, FDOT's HMA production is divided into LOTs. A typical LOT is defined as 4,000 tons (for dense-graded HMA) or 2,000 tons (for open-graded HMA) of asphalt mixture and are further divided into one to four sublots. Most frequently, a normal LOT is divided into four sublots, regardless of the mixture type (dense vs. open graded). Table 4 also shows the frequency of testing for all quality characteristics. As shown in the table, the frequency of testing is one random test per subplot with the exception of roadway density. For roadway density, five random cores are obtained from each subplot and the average density from the five cores are reported as one test result.

Since the implementation of the PWL in 2002, the QA specification has been refined several times based on research and feedback from industry before arriving at the current specification summarized in Tables 4 and 5. Major updates and changes are as follows:

- *July 2019 edition of FDOT Specification*: For the dense-graded HMA, the weight for density was increased from 35 percent to 40 percent while the weight for asphalt binder content was reduced to 20 percent from 25 percent. At the same time, the upper

specification limit for density using vibratory and static mode was widened from 2.0 and 3.0 percent G_{mm} to 3.0 and 4.0, respectively.

- *January 2016 edition of FDOT Specification:* For the dense-graded HMA, the lower specification limit for density using static mode was widened from -1.20 to -1.50 percent G_{mm} .
- *January 2014 edition of FDOT Specification:* For the dense-graded HMA, FDOT removed the allowance of coarse mixtures.
- *July 2005 edition of FDOT Specification:* For dense-graded mixtures, the lower specification limit for density of fine-graded mixtures was widened from -1.00 to -1.20. The air void specification limits for these mixtures were tightened to ± 1.20 from and ± 1.40 . It should be noted that the current FDOT Specification does not consider two separate specification limits for coarse and fine mixtures.
- *July 2005 edition of FDOT Specification:* The small quantity pay table, which is used when a lot has one or two sublots with acceptance data only, specifies incentives.

Table 4. FDOT’s HMA AQC’s and Their Weights.

AQC’s	Weight (%)		Frequency of Testing
	Dense-Graded HMA	Open-Graded HMA	
Roadway Density (% G_{mm})	40	N/A	5 tests / subplot 1 test /subplot
Percent Air Voids	25	N/A	
Asphalt Binder Content	20	40	
Percent Passing 3/8 Inch Sieve	N/A	20	
Percent Passing No. 4 Sieve	N/A	30	
Percent Passing No. 8 Sieve	5	10	
Percent Passing No. 200 Sieve	10	N/A	
Total	100	100	

Table 5. FDOT’s Specification Limits for HMA.

AQC’s	FDOT’s PWL Specification Limits	
	Dense-Graded HMA	Open-Graded HMA
Roadway Density (% G_{mm})	93.00 + 3.00, -1.20 (Vibratory Mode)	N/A
	92.00 + 3.00, -1.50 (Static Mode)	
Percent Air Voids	4.00 \pm 1.20	N/A
Asphalt Binder Content	Target* \pm 0.40	Target* \pm 0.45
Percent Passing 3/8 Inch Sieve	N/A	Target* \pm 6.00
Percent Passing No. 4 Sieve	N/A	Target* \pm 4.00
Percent Passing No. 8 Sieve	Target* \pm 3.10	Target* \pm 2.50
Percent Passing No. 200 Sieve	Target* \pm 1.00	N/A
Note*: These target values are obtained from the approved Mix Designs.		

2.6. OVERVIEW OF SHA PRACTICE

QA specifications have received substantial attention from SHAs as an acceptance method for determining the contractor's degree of compliance with specification requirements. Various surveys of SHAs have revealed the increasing use of QA specifications over the last few decades. A summary of the previous surveys on the use of different asphalt concrete AQC's for pay adjustment systems is shown in Table 6.

The first survey of state DOTs in 1998 reported that out of 19 of the responding agencies that developed a QA specification, 11 of these agencies employed a pay incentive and/or disincentive specification (Elmore et al., 1998). The AQC's that were most frequently used for determining pay factors were asphalt content (by 11 SHAs), in-place density (by 11 SHAs), gradation (by 8 SHAs), VMA (by 5 SHAs), and laboratory-compacted density (by 4 SHAs).

Another survey conducted as part of NCHRP Project 20-5, Topic 35-01 entitled *State Construction Quality Assurance Programs* found that the AQC's in QA programs included asphalt content (reportedly used by 40 SHAs), gradation (by 43 SHAs), and compaction (by 28 SHAs). Other reported AQC's included volumetric properties, ride quality, thickness, and moisture content (Hughes, 2005).

A more recent survey on SHAs' pay adjustment practices was conducted by Hughes et al., (2011) as part of NCHRP Project 10-79. The responses received from 37 SHAs revealed the following.

- Most agencies use weighted composite pay factor equations. The weights and AQC's, however, vary significantly among SHAs.
- The stepped (tabular) and continuous (equation) forms of pay factors are being used equally. Both of these types vary appreciably among agencies.
- Ride quality (i.e., smoothness) is a separate AQC from materials/construction for 27 agencies.
- PWL is the most often used quality measure (used by 16 agencies for one or more AQC's). However, average deviation is the quality measure of choice for ride quality used by 13 agencies.
- The maximum incentives ranging from 1 percent to 15 percent have been specified in most (31 SHAs) specifications, in which 15 percent is used for only Ride Quality. The most commonly used maximum incentive is 5 percent.
- Most agencies have maximum disincentives; many agencies use a remove-and-replace provision, but only a few agencies use a shutdown provision. Different criteria are used for applying a combination of a maximum disincentive, a shutdown provision, and/or a remove-and-replace.
- Two agencies use different weights and acceptance quality characteristics depending on highway classification, e.g., lower classification roads may not include a measure of density.

Table 6. AQC's of Choice by SHAs Identified in Previous Studies.

AQC's	Number of SHAs using AQC		
	Elmore et al. study (1998)	Hughes study (2005)	Hughes et al. study (2011)
Mat Density	NA	28	33
Asphalt Content	11	40	25
Air voids	4	NA	26
Gradation	8	43	19
VMA	5	NA	12
Other Volumetrics	NA	NA	4
Joint density	NA	NA	8
Thickness	NA	NA	9

Because the most recent survey results in the literature were published nearly a decade ago (i.e., in 2011), the research team compiled other SHA's QA specifications on acceptance criteria and pay adjustments. This information is summarized in Appendix A.

Figure 9 shows the distribution of quality measures used by SHAs. As shown in the figure, PWL is used by 30 SHAs in their pay adjustment systems, which when compared to 16 states using PWL based on the 2011 survey clearly indicates the SHAs' move toward PWL. It is also noted that one SHA (New York) employs both PWL and AAD.

Figure 10 shows all SHAs use mat density as an AQC, more than 30 SHAs use asphalt content and air voids as material AQC's, and 3 SHAs use material and construction CPF's containing ride quality AQC's.

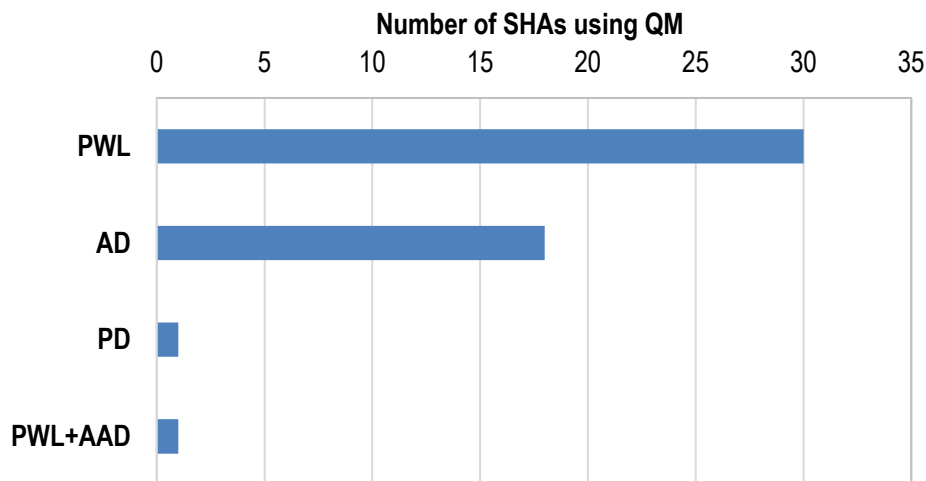


Figure 9. Quality Measures (QMs) of Choice by SHAs.

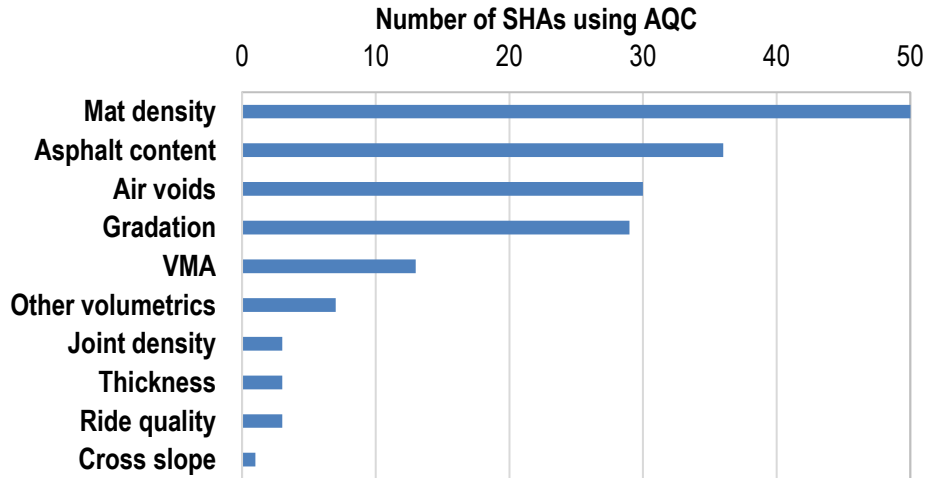


Figure 10. Acceptance Quality Characteristics (AQC) of Choice by SHAs.

2.6.1. Practice of Select SHAs for Acceptance of Open Graded Friction Course (OGFC)

FDOT specifies the use of open-graded friction course (OGFC) on all multi-lane, high-speed facilities. As such, it is of interest to summarize the other SHAs’ practice and experience pertaining to acceptance and performance of OGFCs.

OGFC is a thin, permeable layer of asphalt concrete that is designed to have high air voids (typically 15 to 20 percent) by using a larger percentage of coarse aggregate and a lower percentage of fine aggregate (usually less than 20 percent of the material passes the No. 8 sieve). OGFCs have relatively high binder content while optimum asphalt binder content should be selected based upon balancing durability (i.e., prevent raveling and delamination) and draindown potential. With the high asphalt binder contents and large percentage of coarse aggregate, a stabilizing additive is used to hold the asphalt binder within the mixture during storage, transportation, and placement. Eliminating draindown can be achieved by modifying the asphalt binder (i.e., polymer modified or rubberized asphalt) and/or the use of fibers. By interconnecting the voids, OGFC provides improved surface drainage during rainfall. In addition to minimizing hydroplaning potential and providing improved friction values on wet pavements, the OGFC reduces vehicle splash and spray behind vehicles, enhances visibility of pavement markings during wet weather, and may potentially reduce tire-pavement noise.

OGFC which is also referred to as Permeable Friction Course (PFC) has gained wide acceptance by the southern and western states in the U.S. From quality acceptance and payment scheduling perspective, gradation and binder content are the two primary material AQC’s required by those SHAs that pave any type of OGFCs. Draindown, air voids, and Rice gravity are the material AQC’s included in some SHAs specifications.

The purpose of compaction for OGFCs is slightly different than for typical asphalt concrete. Unlike a typical asphalt concrete, OGFCs are not compacted for the purpose of meeting some

specified density. Therefore, SHAs require a certain type of roller and compaction method with no specific density requirement. As such, mat density of OGFCs is rarely checked. If it is desired to verify the adequacy for water drainage, determining in-place air voids is more critical than density. As such, a field permeability test on the compacted mat at the time of construction is required in some foreign countries (e.g., Belgium and Spain, Argentina, and Japan).

The following sections provide an overview of select SHAs for acceptance of OGFCs while the focus has been given to their pay adjustment system.

2.6.1.1. Georgia Department of Transportation

The Georgia Department of Transportation (GDOT) has used OGFCs since the 1950s as a thin, porous wearing layer primarily on Interstate highways. The early mixes were very susceptible to draindown and premature failure due to weathering, and therefore GDOT placed a moratorium on the use of OGFC in 1982. Since that time, several modifications (such as using hydrated lime, fiber, polymer modified binder, and coarser aggregate gradations) have been made to improve the performance of OGFC mixes. These modifications resulted in significant improvements in the performance of OGFCs in the state of Georgia. Thus, in the early 1990s, the GDOT developed the 12.5 mm OGFC, which is now the standard GDOT mix and has been used extensively statewide since 1993 (Watson et al., 1998; Mallick et al., 2000). Currently, 12.5 mm and 9.5 mm OGFCs are designed and paved in the state of Georgia (GDOT, 2013).

As shown in Table 7, aggregate gradation and binder contents are the AQC's for acceptance and payment scheduling of OGFC mixtures in GDOT's standard specifications. It should be mentioned that only two sieve sizes (3/8 Inch and No. 8 sieves for 12.5 mm and No. 4 and No.8 sieves for 9.5 mm OGFCs) are specified as control sieves for determining the pay factors. GDOT's Standard Specification uses AAD and tabulated pay factors for determination of payment, and the maximum pay factor cannot exceed 1.0. In addition, when two or more pay factors for a specific acceptance lot are less than 1.0, the adjustment factor is the lowest pay factor (GDOT, 2013).

Table 7. GDOT's AQC's and Specification Limits for OGFCs.

AQC's	Design Limits		Specification Limits
	9.5 mm OGFC	12.5 mm OGFC	
Asphalt Binder Content (%)	6.0 – 7.25	5.75 – 7.25	±0.4
Percent Passing 3/4 Inch Sieve	–	100	±0.0
Percent Passing 1/2 Inch Sieve	100	85.0 – 100	±6.1
Percent Passing 3/8 Inch Sieve	85.0 – 100	55.0 – 75.0	±5.6
Percent Passing No. 4 Sieve	20.0 – 40.0	15.0 – 25.0	±5.7
Percent Passing No. 8 Sieve	5.0 – 10.0	5.0 – 10.0	±4.6
Percent Passing No. 200 Sieve	2.0 – 4.0	2.0 – 4.0	±2.0
Draindown (%)	< 0.3	< 0.3	–

2.6.1.2. Maryland Department of Transportation

OGFCs were used significantly by the Maryland Department of Transportation (MDOT) in the late 1980s and early 1990s to reduce hydroplaning and pavement noise (Stanard et al., 2007). Maryland DOT’s standard specification specifies three types of OGFCs, namely 9.5 mm OGFC, 12.5 mm OGFC, and 12.5 mm Porous European Mix (PEM) as shown in Table 8. The PWL, which is referred to as Percent Within Specification Limit or PWSL in Maryland’s specification, for each AQC’s along with their associated pay adjustment factors shown in Table 9 are used to determine the composite pay factor (Maryland DOT, 2019).

Table 8. Maryland DOT’s AQC’s and Specification Limits for OGFC’s and PEM.

AQC’s	Design Limits			Specification Limits
	9.5 mm OGFC	12.5 mm OGFC	12.5 mm PEM	
Asphalt Binder Content (%)	6.0 – 7.25	5.75 – 7.25	5.5 – 7.0	±0.4
Percent Passing 3/4 Inch Sieve	–	100	100	±0.0
Percent Passing 1/2 Inch Sieve	100	85.0 – 100	80.0 – 100	±6.0
Percent Passing 3/8 Inch Sieve	85.0 – 100	55.0 – 75.0	35.0 – 60.0	±5.5
Percent Passing No. 4 Sieve	20.0 – 40.0	15.0 – 25.0	10.0 – 25.0	±6.0
Percent Passing No. 8 Sieve	5.0 – 10.0	5.0 – 10.0	5.0 – 10.0	±4.5
Percent Passing No. 200 Sieve	2.0 – 4.0	2.0 – 4.0	1.0 – 4.0	±2.0
Draindown (%)	< 0.3	< 0.3	< 0.3	–

Table 9. Pay Factors in Maryland DOT Specification.

AQC’s	Pay Factor
Asphalt Binder Content (%)	64
Percent Passing 3/8 Inch Sieve	9
Percent Passing No. 4 Sieve	9
Percent Passing No. 8 Sieve	9
Percent Passing No. 200 Sieve	9

2.6.1.3. Mississippi Department of Transportation

Mississippi’s first OGFC test sections were built in the 1970’s with local aggregate and neat asphalt. These sections performed poorly and experienced severe raveling and stripping. Consequently, the use of OGFC in Mississippi was discontinued until 2007 when a test section of OGFC with polymer modified binder was constructed on I-55. The outcome of a research study in 2009 revealed that this test section can carry significant traffic while maintaining an adequate level of in situ permeability. It was concluded that OGFC’s can be designed successfully using Mississippi’s local aggregates and polymer modified asphalt (White and Ivy, 2009; White and Hillabrand, 2013).

There are two types of OGFCs (12.5 mm and 9.5 mm) indicated in the Mississippi DOT’s standard specifications. The AQCs and specification limits are shown in Table 10. In addition to gradation and binder content, air voids at N_{Design} is also used as an AQC. Mississippi DOT applies the minimum single pay factor shown in Table 11 and uses AAD for the QM determination (Mississippi DOT, 2017).

Table 10. Mississippi DOT’s AQCs and Specification Limits for OGFCs.

AQCs	Design Limits		Specification Limits	
	9.5 mm OGFC	12.5 mm OGFC	JMF Limits	Warning Limits
Asphalt Binder Content (%)	Minimum obtained based on aggregate bulk specific gravity		-0.3 to +0.5	-0.2 to +0.4
Percent Passing 1/2 Inch Sieve	100	100	±4.0	±3.0
Percent Passing 3/8 Inch Sieve	90.0 – 100	80.0 – 89.0	±4.0	±3.0
Percent Passing No. 4 Sieve	15.0 – 30.0	15.0 – 30.0	±3.0	±2.0
Percent Passing No. 8 Sieve	10.0 – 20.0	10.0 – 20.0	±3.0	±2.0
Percent Passing No. 200 Sieve	2.0 – 5.0	2.0 – 5.0	±1.5	±1.0
Total Voids at N_{Design} of 50 gyrations (%)	Minimum 15%		-1.3 to +2.5	-1.0 to +2.0

Table 11. Mississippi DOT’s AQCs and Specification Limits for OGFCs.

AQCs	Produced in Warning Bands	Produced Outside JMF Limits
Gradation	0.90	0.5
Binder content	0.85	0.5
Total Voids at N_{Design}	0.70	0.5

2.6.1.4. South Carolina Department of Transportation

The South Carolina DOT (SCDOT) has been using OGFCs since the mid-1970s to reduce accidents on high volume roads. A comprehensive research study was conducted by SCDOT in cooperation with FHWA to identify methods to improve the design, performance, construction, and maintenance of OGFCs in South Carolina (Putman, 2012). This study led to several recommendations on the mix design procedure and alternative aggregate gradation, the procedure for determining the necessary thickness of OGFC layers, as well as the best practices for construction and maintenance of OGFCs.

SCDOT uses PWL as QM and considers gradation and binder contents as AQCs for OGFC mixtures acceptance and payment scheduling. Table 12 summarizes SCDOT’s most recent specification limits. The pay factor for binder content is calculated using the continuous AASHTO equation (i.e., Equation 4). However, the gradation pay factor is determined based on the number of out of tolerance gradations as shown in Table 13 (SCDOT, 2007).

Table 12. SCDOT's AQC's and Specification Limits for OGFCs.

AQC's	Specification Limits	Weight (%)
Asphalt Binder Content (%)	5.5 – 7.0	50
Percent Passing 3/4 Inch Sieve	100	50
Percent Passing 1/2 Inch Sieve	85.0 – 100	
Percent Passing 3/8 Inch Sieve	55.0 – 75.0	
Percent Passing No. 4 Sieve	15.0 – 25.0	
Percent Passing No. 8 Sieve	5.0 – 10.0	
Percent Passing No. 200 Sieve	0.00 – 4.0	

Table 13. Pay Factor for Gradations in SCDOT Specification.

Number of out of tolerance gradations per LOT	Pay Factor
0	100
1	90
2	75
3 or more	50

2.6.1.5. Utah Department of Transportation

During a meeting of the Utah Transportation Research Advisory Council (UTRAC) in 1993, several Materials and Maintenance Engineers of the Utah Department of Transportation (UDOT) identified the premature failure of open-graded surface courses (OGSCs). In order to identify the source of premature failures and improve the durability of OGSCs in the State of Utah, UDOT supported a research study conducted by Utah State University. The major findings from this study suggested that it is important for UDOT to review, and where necessary, revise the policy for OGSCs. As such a micro-level review of the materials, construction, and maintenance specifications was recommended (Seneviratne and David, 1996).

UDOT's current standard specifications require binder content and gradations for acceptance and pay adjustment while it does not specify a design limit for binder content (Table 14). PWL is the QM of choice by UDOT for gradation along with the use of a tabular pay factor. However, incentive/disincentive for asphalt binder content is computed based on Table 15 using the single test result with the largest deviation from the target. The pay adjustment for both gradation and binder content is determined in dollar per ton (UDOT, 2017).

Table 14. UDOT’s AQCs and Specification Limits for OGSCs.

AQCs	Design Limits	Specification Limits
Asphalt Binder Content (%)	NA	Multiple specification limits
Percent Passing 1/2 Inch Sieve	100	NA
Percent Passing 3/8 Inch Sieve	90.0 – 100	Target Value ± 6.0 percent
Percent Passing No. 4 Sieve	35.0 – 45.0	Target Value ± 6.0 percent
Percent Passing No. 8 Sieve	14.0 – 20.0	Target Value ± 5.0 percent
Percent Passing No. 200 Sieve	2.0 – 4.0	Target Value ± 2.0 percent

Table 15. Pay Adjustment for Gradations in UDOT Specification.

Binder Content	Pay Adjustment in \$/ton OGSC
Within ± 0.30% of target	1.00
Between ± 0.31% and ± 0.45% of target	0.00
Between ± 0.46% ± 0.60% of target	-2.00
Greater than ± 0.61%	Reject

2.7. SUMMARY

This chapter provides a summary of the literature review conducted on SHAs’ practices for quality-based pay adjustment systems for pavement construction acceptance. The components as well as the process needed for developing the quality-based pay adjustment system were thoroughly reviewed. In addition, this chapter provides an overview of Performance Related Specifications, as well as the components and processes required for developing quality-based pay adjustment systems.

Due to the lack of a recent survey or synthesis of agency practices, the literature review was also extended to gathering and reviewing other agencies’ specifications. This effort revealed that many agencies are moving towards implementing the PWL (or PD) for their acceptance specifications. Nonetheless, the AQCs, as well as the weights used for calculating CPF (if used), varied significantly among SHAs.

FDOT’s PWL specification for acceptance and payment of HMA materials was first implemented in 2002, with the AQCs and weights that were established empirically based on past experience and engineering judgement (i.e., not necessarily based on their relationship to long-term pavement performance). Although FDOT’s AQCs are commonly used by other agencies, the literature review did not reveal any evidence of an agency showing the relationship between these common AQCs (and weights) and long-term pavement performance.

3. DATA GATHERING

3.1. INTRODUCTION

As discussed in the previous chapter, FDOT's PWL specification for acceptance and payment of HMA was implemented with the AQC's and their weights established empirically based on past experience and engineering judgement. Although FDOT's AQC's are among those commonly used by other SHAs, the literature review did not reveal any evidence of an agency showing the relationship between these common AQC's (and weights) and long-term pavement performance.

This chapter documents the data gathering efforts and the data elements that were made available to the research team for assessing the level of impact that FDOT's incentive specification has on long-term performance of asphalt pavements.

3.2. DATA ELEMENTS

3.2.1. Pay Factor Data

For this study, FDOT provided the research team with a list of 68 projects that were constructed between years 2004 and 2006 (i.e., approximately 12 to 14 years old at the time of this study) with LOTs having a wide range of PF values. Figure 11 shows a map of the project locations.

More specifically, the data included 40 projects (261 LOTs & 841 sublots) for dense-graded mixtures and 33 projects (189 LOTs & 644 sublots) for open-graded mixtures (with 5 projects including both dense- and open-graded mixtures). FDOT also provided the as-built plans, pay factor worksheet, Quality Control (QC) and verification reports for all 68 projects.

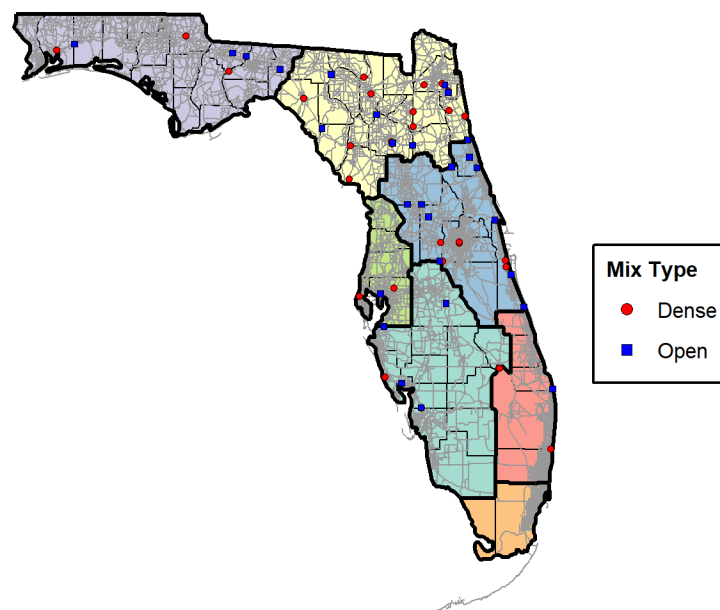


Figure 11. Location of Projects Identified for this Study.

The data provided by FDOT (i.e., the as-built plans, pay factor worksheets, and the QC reports) were in scanned image formats (i.e., .tif files). As such, the following data elements were obtained from the image files and manually entered into an Excel database.

1. General Project Information
 - a. FDOT Financial Project Number (FIN)
 - b. District, County, and State Route number
 - c. County section number
 - d. Limiting mileposts for overall project
 - e. Contractor name
2. LOT & Sublot Information
 - a. LOT/sublot number and verification sublot number
 - b. Tonnage (Intended and actual)
 - c. Construction dates (start, end, and reported dates)
 - d. Plant number
 - e. Mix type and mix design number
 - f. Target Acceptance Quality Characteristics (AQC's)
 - g. Achieved AQC's (mean and standard deviation)
 - h. Upper quality index (QU) and lower quality index (QL) for each AQC
 - i. PWL and PF values for each AQC
 - j. Station limits for each sublot (Note: the stations were converted to mileposts using the station-to-milepost conversion equation obtained from the as-built plans)

Figure 12 and Figure 13 show the range of CPF values within each project for dense and open graded mixtures, respectively. These figures clearly show that most of the projects exhibit a relatively wide range of CPF values which is desired for this study. However, a few projects (e.g., FIN 197767-2 in Figure 12) are showing a narrow CPF range. This is because the data for some of the sublots (e.g., the individual PF values and/or AQC results) were missing and these sublots had already been eliminated during the manual data entry process.

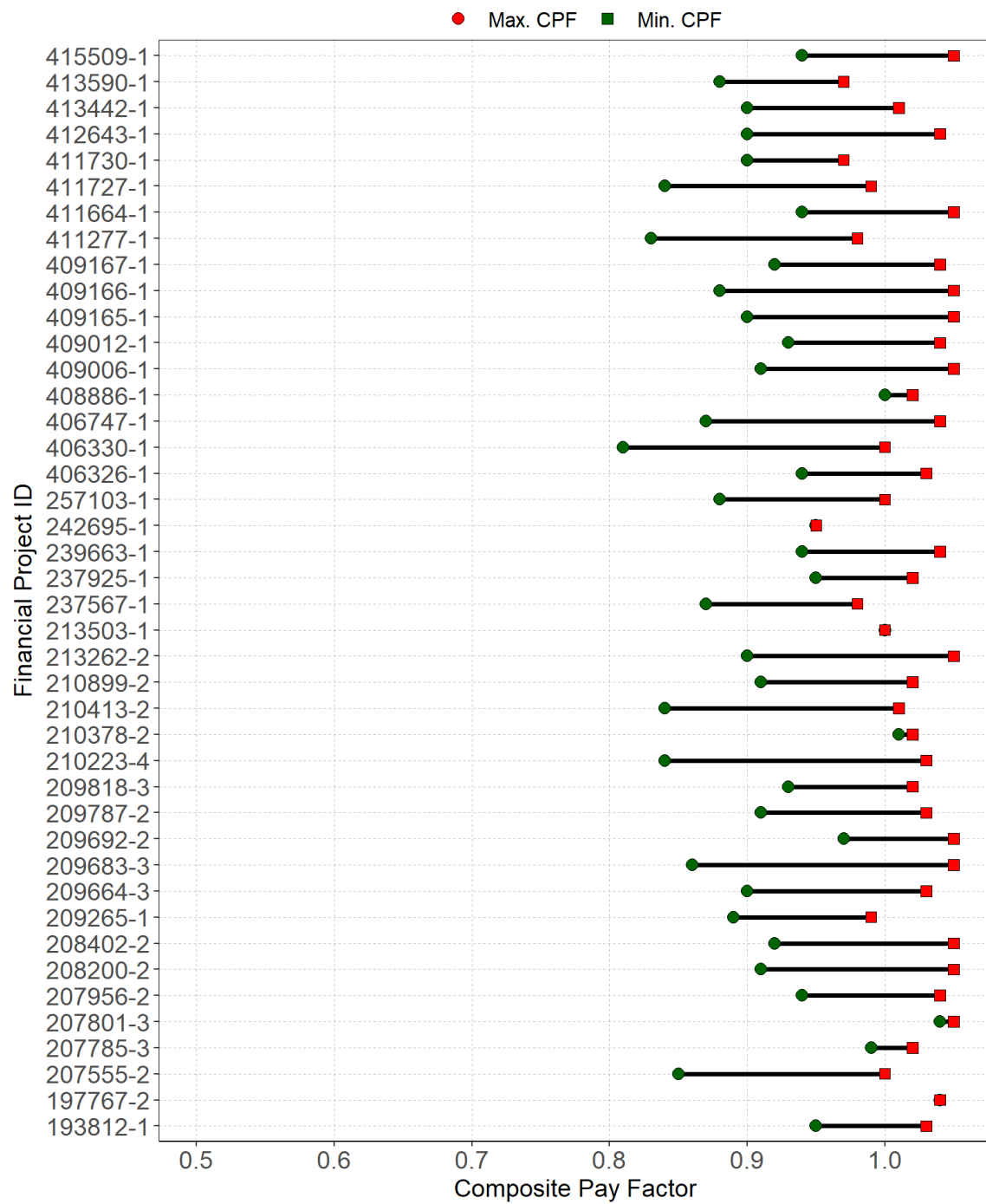


Figure 12. Range of Composite Pay Factors for Dense Graded Mixes.

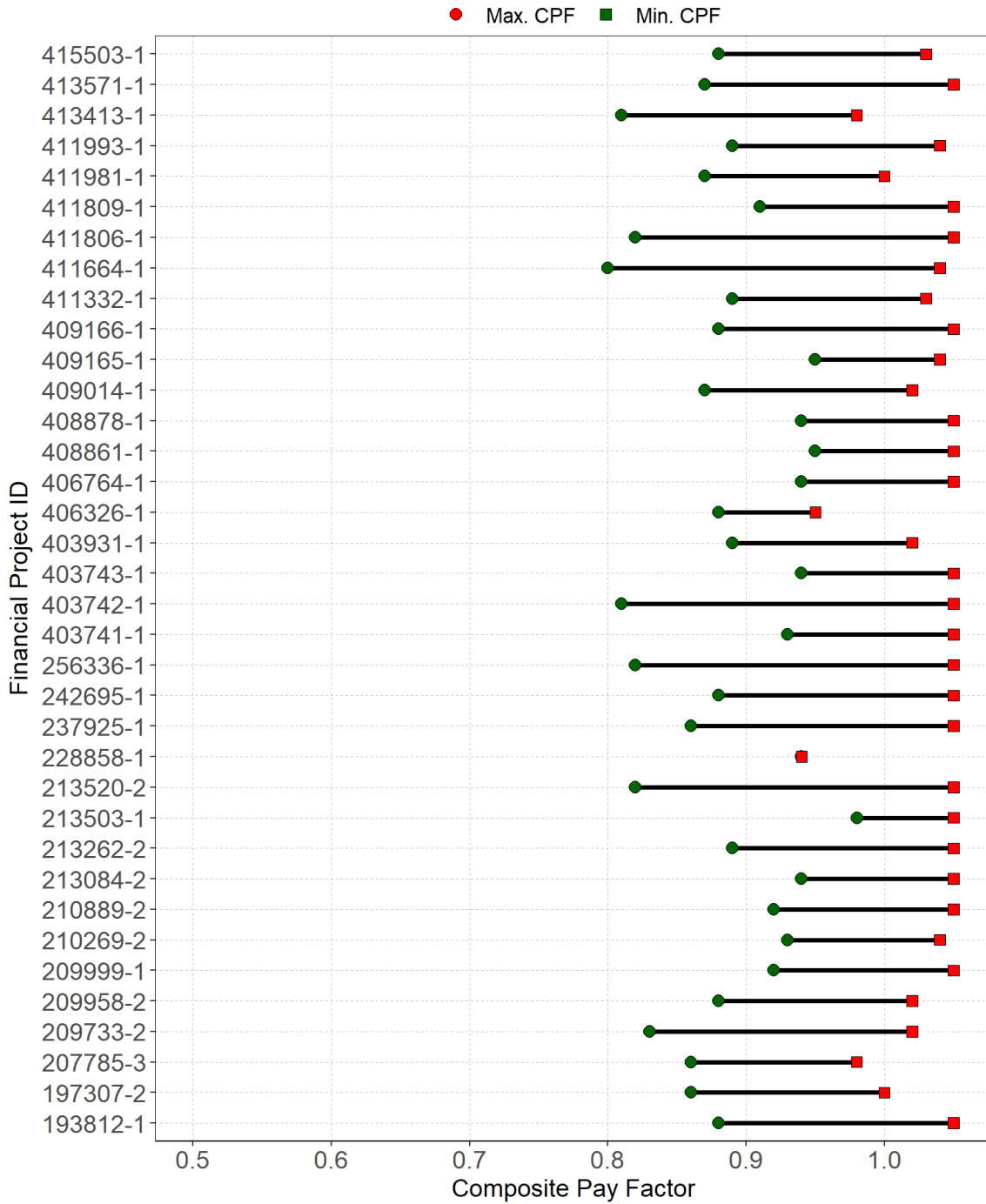


Figure 13. Range of Composite Pay Factors for Open Graded Mixes.

After the Excel database has been constructed, it became evident that some projects needed to be eliminated due to the lack of station information for the LOTs and/or the station-to-milepost conversion equation. In addition, a couple of projects that included only a single LOT had also been eliminated. The following summarizes the sections that remained available for the study after the initial data screening.

1. Dense-graded mixtures: 32 Projects (221 LOTs & 688 Sublots)
2. Open-graded mixtures: 28 Projects (165 LOTs & 568 Sublots)

As a summary of the remaining data, Figure 14 and Figure 15 show the distribution of the Composite Pay Factor (CPF) as well as the individual PF values for dense and open graded mixtures, respectively.

While these figures clearly show a wide distribution of PF values (from 0.55 to 1.05), they also show that the distributions are not normal. In addition, the PF value of 1.0 is dominant in all AQC's, with some of the AQC's showing additional peaks. For example, Figure 14 indicates that for dense graded mixtures, asphalt binder content and percent air voids show an additional peak at PF value of 0.8, while the density and CPF show a secondary peak at PF value 1.05. Similarly, in the case of the open graded mixtures (Figure 15), additional peaks occur at PF values of 0.8 (for passing 3/8 in. sieve, passing No. 4 sieve, and asphalt binder content) or 1.05 (for passing No. 8 sieve).

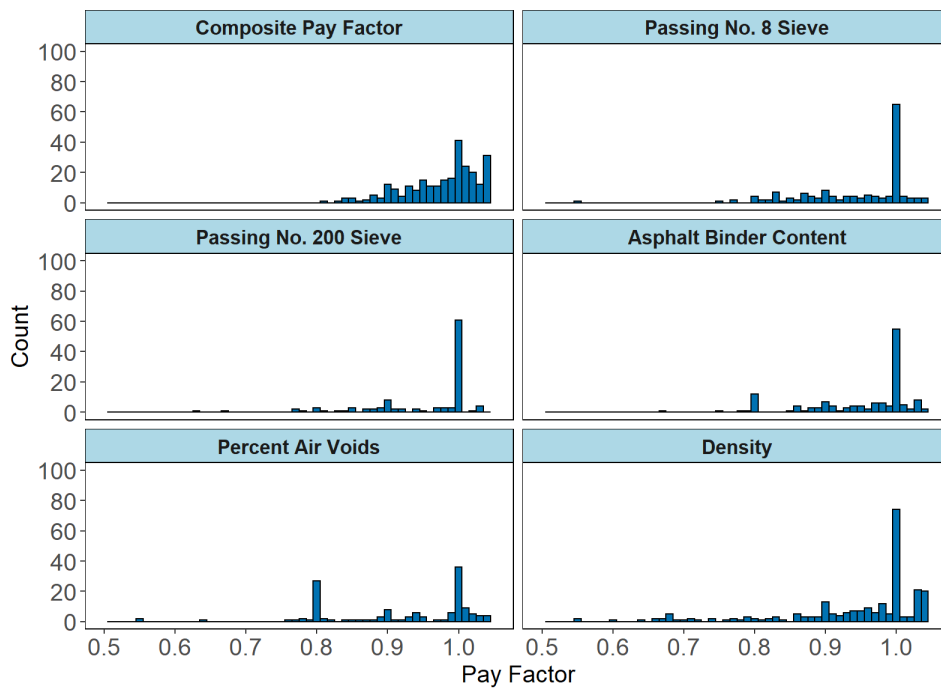


Figure 14. Distribution of Pay Factors for Dense Graded Mixtures.

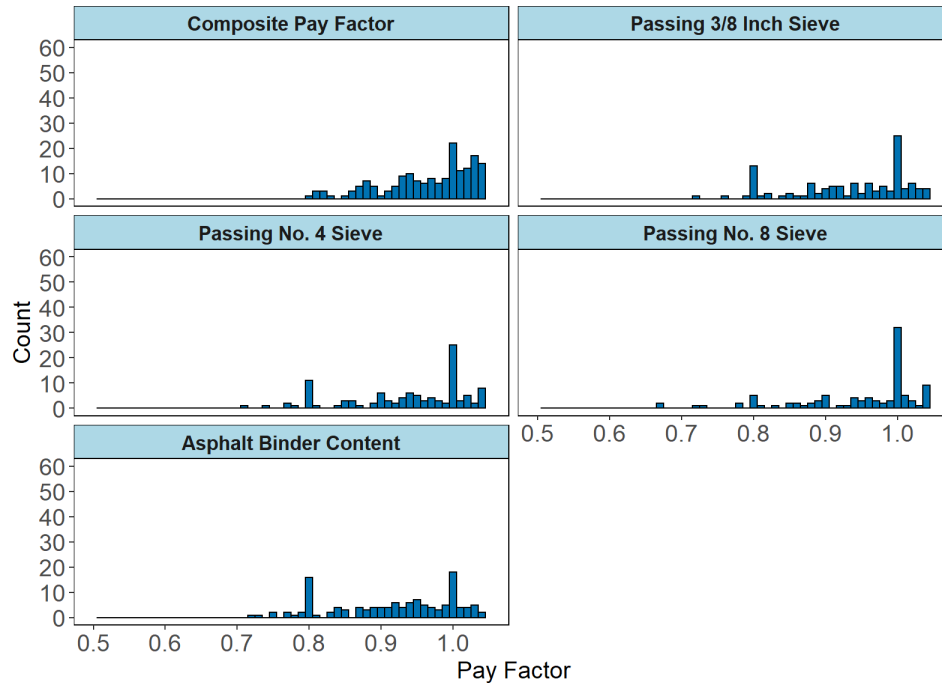


Figure 15. Distribution of Pay Factors for Open Graded Mixtures.

3.2.2. Mix Design Data

For each of the mixtures identified in the Excel database, FDOT also provided the research team with the asphalt mix design spreadsheet. The following information was extracted from each mix design spreadsheet.

1. Traffic level
2. Binder grade
3. Major aggregate type (Granite vs Limestone)

3.2.3. Traffic Data

FDOT also provided the research team with Average Daily Traffic (ADT) and percent (%) trucks (also known as the T-Factor in FDOT's system) for their entire roadway network corresponding to the year 2020.

Based on the Roadway ID and the milepost limits in the Excel database, the ADT and the T-Factor for each LOT within the Excel database were extracted and used to calculate the Average Daily Truck Traffic (ADTT).

3.2.4. Distress Data

The pavement distresses of interest for the purpose of this study are: Cracking, Rutting, and Raveling. Although these distresses (and their histories since construction) could have been

obtained from FDOT’s Pavement Condition Survey (PCS) database, the Department recommended not to use the PCS data due to the following reasons.

1. Although the PCS data is collected annually on the entire FDOT roadway system, the purpose of this data is to support the pavement management activities at the network level. As such, the distress data is typically summarized over the entire length of a project (rather than LOTs or sublots). I.e., the PCS database does not have the granularity to distinguish the performance of a specific LOT (or sublot) from another LOT within the same project.
2. The PCS database uses a rating system (rather than the actual amount of distresses) for assessing the pavement condition. More specifically, the database includes Crack Rating, Rut Rating, and Ride Rating, all of which ranges from 0 to 10 scale (with 10 being the best condition). While the Rut Rating is determined based on the average rut depth in the wheel paths, the Crack Rating is determined visually from windshield surveys. In other words, the Crack Rating is inevitably subjective to a certain degree (despite the rigorous process FDOT goes through for qualifying their “raters”).

It is recognized that pavement distress data is one of the most crucial data elements for this study. As such, the research team initially requested the Department to collect detailed pavement distress data using their high-speed Laser Crack Measurement System (LCMS) equipment on LOTs included in the Excel database. However, this was found to be unachievable within the allowed time for the project, and it was necessary to reduce the amount of LOTs (and sublots) to be surveyed for pavement distress.

Therefore, the research team and the Department reviewed the locations of the LOTs (and sublots) to eliminate any unnecessary LOTs for the study (if any) and to plan for an efficient data collection. This review revealed that many LOTs in the multi-lane projects (especially for the open graded mixtures) were located in the passing lanes. After a further review of the PF data, it was agreed to eliminate the LOTs located in the passing lanes entirely (rather than eliminating certain number of projects completely). The following summarizes the final number of projects, LOTs, and Sublots that remained available for this study.

1. Dense-graded mixtures: 28 Projects (138 LOTs & 311 Sublots)
2. Open-graded mixtures: 17 Projects (58 LOTs & 123 Sublots)

Pavement distress data for the above LOTs were collected between December, 2020 and January, 2022. A summary of the gathered distress data is provided in the following.

3.2.4.1. Cracking

The data for pavement cracking was collected using FDOT’s LCMS system and analyzed using their automated distress algorithm. The automated algorithm was set up to report the following.

1. Fatigue cracks: Low, medium, and high severity.

2. Longitudinal cracks within and outside the wheel paths: Hairline, low, medium, and high severity.
3. Transverse cracks: Hairline, low, medium, and high severity.
4. Block cracking: Hairline, low, medium, and high severity.
5. Patching with low, medium, and high severity deterioration.

Despite the 13+ years of pavement age (i.e., all the projects were constructed in 2006 or earlier), the LCMS cracking data immediately revealed that these sections were mostly performing very well, with the majority of the sublots showing no cracks at all.

To better assess the amount of cracking (if any) observed from the surveyed sublots, the total area affected by the above cracks was calculated for each subplot (Note: a unit width of 1.0 ft. was assumed for longitudinal and transverse cracks for this purpose). Then, the percent (%) cracked lane area was calculated as:

$$\text{Percent (\%) Cracked Lane Area} = \text{Total Cracked Area} / \text{Total Lane Area} (\times 100) \quad (11)$$

In the subsequent sections of the report, the term “Total Cracking” will be used to indicate the “Percent Cracked Lane Area”, unless noted otherwise.

Figure 16 shows distribution of total cracking observed in the sublots. The figure confirms that most of the sublots are performing very well. More specifically, it indicates that the over 50 percent of the sublots exhibited no cracking regardless of the mix type (Dense or Open). In addition, approximately 77 percent of dense graded sublots and 87 percent of open graded sublots showed less than or equal to 5 percent of the lane area with cracks.

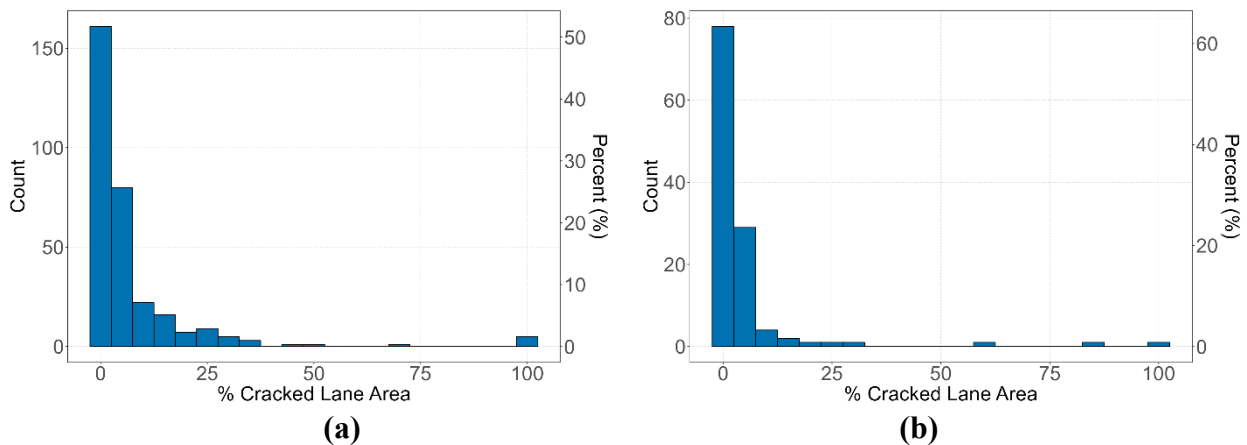


Figure 16. Distribution of Total Cracking for (a) Dense and (b) Open Graded Mixtures.

3.2.4.2. Rutting

As for rutting, the LCMS system reported the average rut depth calculated from both wheel paths for each subplot. Figure 17 shows the rut depth distribution, which clearly indicates that these sublots are performing well in terms of rutting as well. More specifically, 57 percent of dense

graded sublots and 51 percent of open graded sublots showed less than or equal to 0.1-inch of rut.

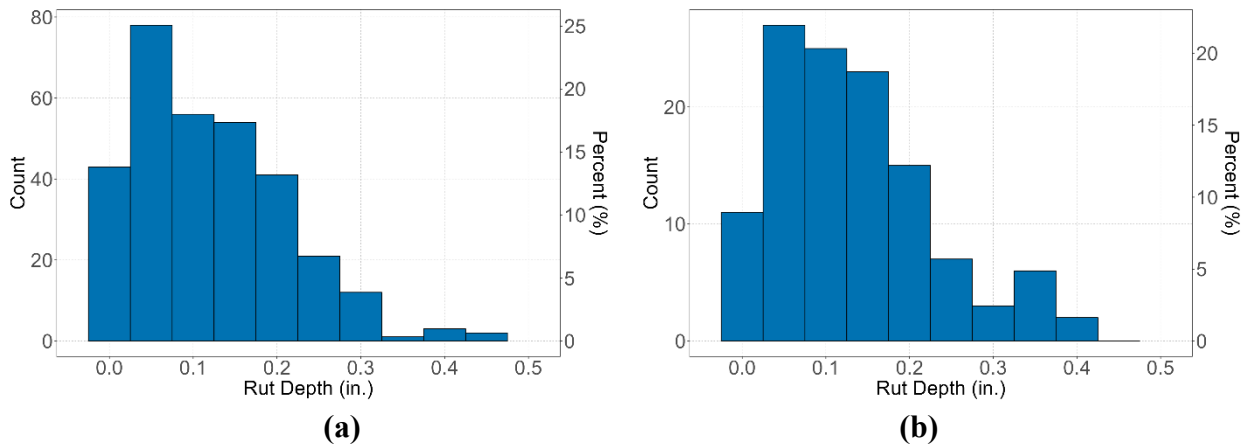


Figure 17. Distribution of Rut Depth for (a) Dense and (b) Open Graded Mixtures.

3.2.4.3. Raveling

Raveling within the sublots were quantified by the Raveling Index (RI) that was built into the LCMS analysis libraries. According to the LCMS raveling module, the RI can be used to distinguish varying levels of raveling, as shown in the following.

- No Raveling: $RI < 200$
- Low (or Light) Raveling: $200 \leq RI \leq 290$
- Medium (or Moderate) Raveling: $290 < RI \leq 475$
- High (or Severe) Raveling: $RI > 475$

Figure 18 shows the distribution of RI values obtained from LCMS. Clearly, the majority of the sublots are showing no raveling. More specifically, 93 percent of dense graded sublots and 82 percent of open graded sublots are showing RI values of less than or equal to 200 (i.e., no raveling based on the RI threshold shown above).

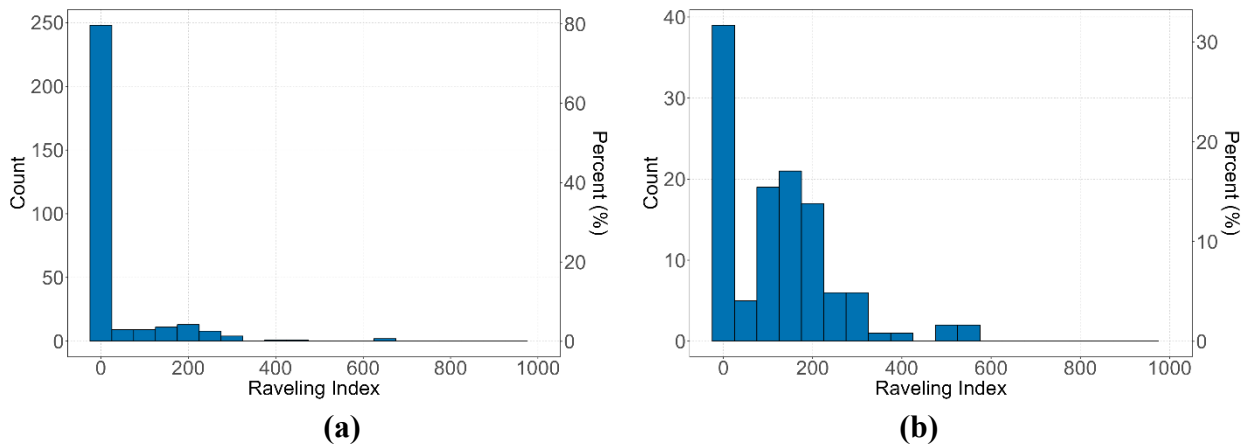


Figure 18. Distribution of Raveling Index for (a) Dense and (b) Open Graded Mixtures.

3.3. COMPREHENSIVE DATABASE

The data elements discussed in the previous section of the report were merged into the PF database. The resulting database, referred to as the “Comprehensive Database”.

The purpose of the comprehensive database was to allow for the analysis of PF data at two different levels, described as the following.

1. Project level analysis: The project level analysis (or project-by-project analysis) was planned to determine if the PF values had an impact on pavement performance while eliminating the effect of other variables (e.g., traffic, thickness of Asphalt Concrete [AC], binder grade, aggregate type, etc.).
2. Network level analysis: The network level analysis was intended to determine if an overall trend between PF and long-term pavement performance could be established statistically.

As mentioned previously, the number of sublots included in the comprehensive database (i.e., 311 sublots for dense and 123 sublots for open) was a significant reduction from the number of sublots that were available before the distress data collection (i.e., 688 sublots for dense and 568 sublots for open). As such, it was deemed important to ensure that the PF values available for the study still exhibit a wide range.

Figure 19 and Figure 20 show the distribution of PF values based on the data that are included in the comprehensive database (i.e., those that have pavement distress data available for the study) for dense and open graded mixtures, respectively. These figures clearly show that the PF values still span a wide range with the dominant PF values (especially the PF value of 1.00) preserved (comparing Figure 19 to Figure 14, and Figure 20 to Figure 15).

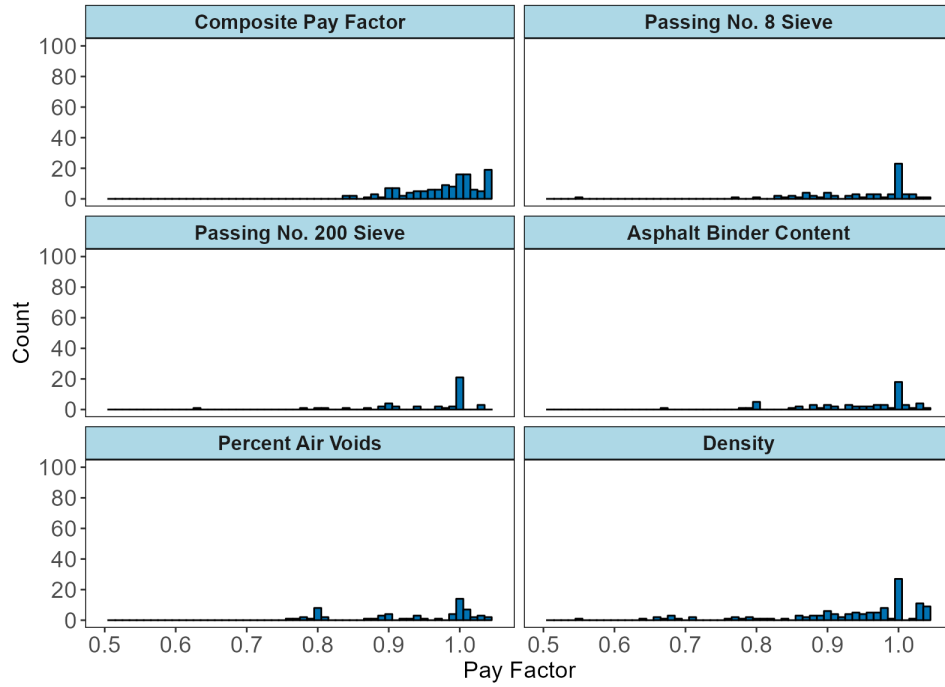


Figure 19. Distribution of Pay Factors for Dense Graded Mixtures in the Comprehensive Database.

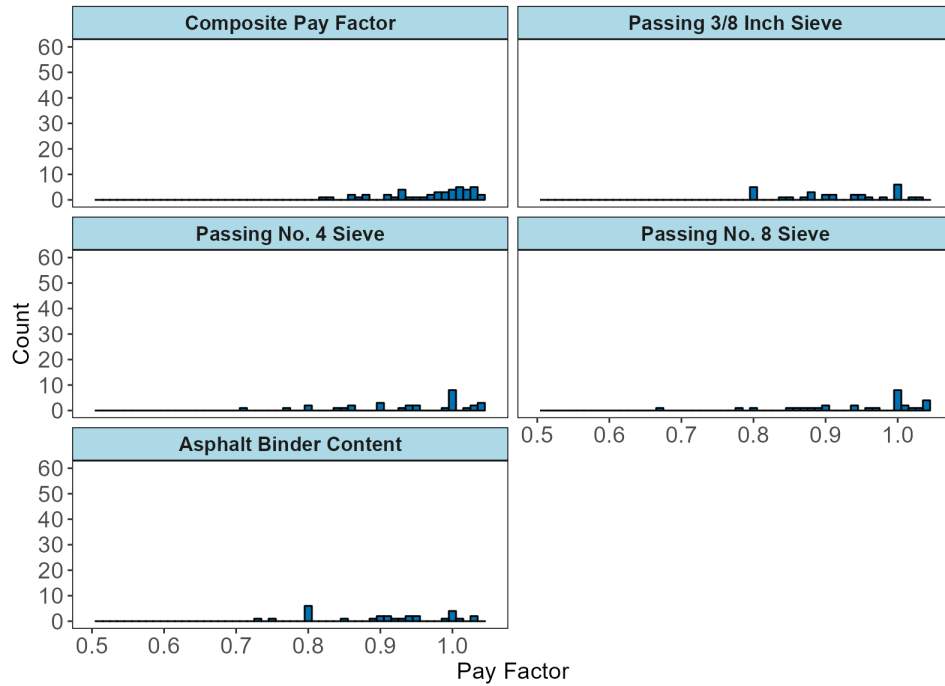


Figure 20. Distribution of Pay Factors for Open Graded Mixtures in the Comprehensive Database.

4. PRELIMINARY ANALYSIS AND CHALLENGES

This chapter provides an overview of the preliminary statistical analyses performed both at the project level and at the network level.

In summary, the traditional statistical analysis methods such as regression and Analysis of Variance (ANOVA) did not provide much insight into the relationship between the PF and the performance data. As such, this chapter of the report shall be kept relatively brief and focus on presenting the challenges associated with the gathered data.

4.1. PROJECT LEVEL ANALYSIS

As discussed in the previous chapter of this report, the project level analysis was planned to assess the impact of CPF on pavement performance by analyzing the data on a project-by-project basis. Initially, a two-step, bottom-up approach had been proposed for the project level analysis, as described in the following.

1. Assess the impact of CPF data from each project independently. The underlying idea behind this was that the structural design and mixture design parameters (e.g., traffic, AC thickness, binder grade, etc.) are relatively homogenous within a given project. In other words, it was anticipated that the analysis would have assisted in reducing the unknown effects caused by external factors such as those mentioned previously.
2. If the project-by-project analysis of the CPF data from the previous step provided reasonable trends, then determine if a feasible trend can be established for a group of projects categorized by different aggregate types (limestone vs. granite), traffic level, binder grade, etc.

Although the research team had hoped that the above-mentioned analysis approach would reveal an in-depth insight into the effect of CPF, the team immediately faced a challenge with the gathered data. Figure 21 and Figure 22 show examples of the relationship between project level CPF and total cracking, for dense and open graded mixtures, respectively. While these projects showed a fairly wide range of CPF values, the amount of distress was relatively uniform and caused the regression analysis to yield very poor correlations ($R^2 < 0.1$).

Although these were only a couple of examples, the majority of the projects showed similar trends (at best). The project level plots for cracking, rutting, and raveling of dense graded mixtures are provided in Appendices B, C, and D, respectively. The corresponding plots for open graded mixtures are provided in Appendices E through G.

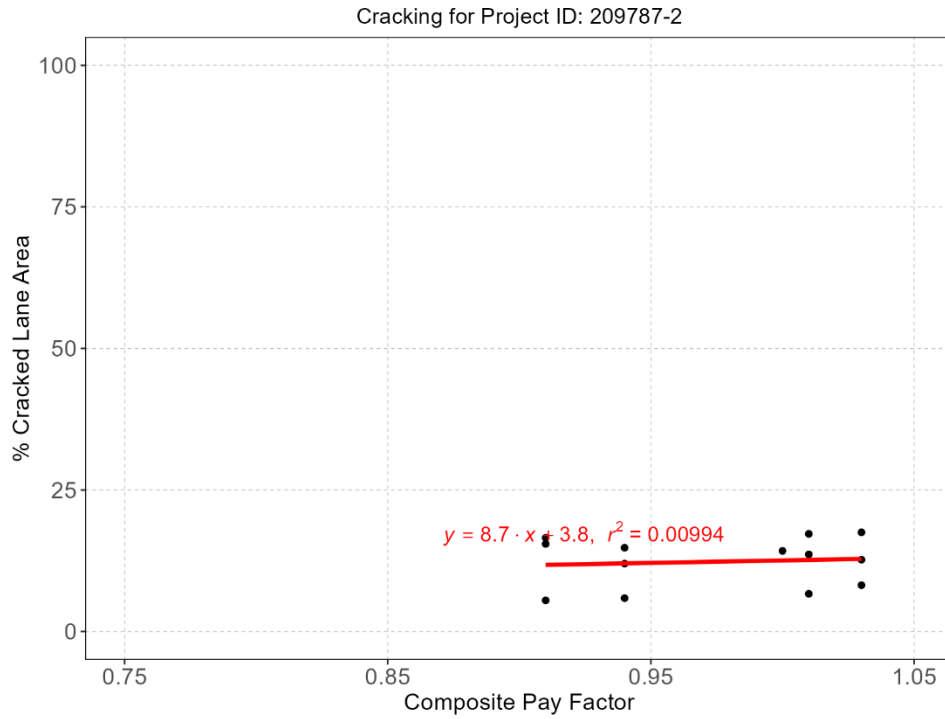


Figure 21. Example Cracking vs CPF Trend for Dense Graded Mixture (Project 209787-2).

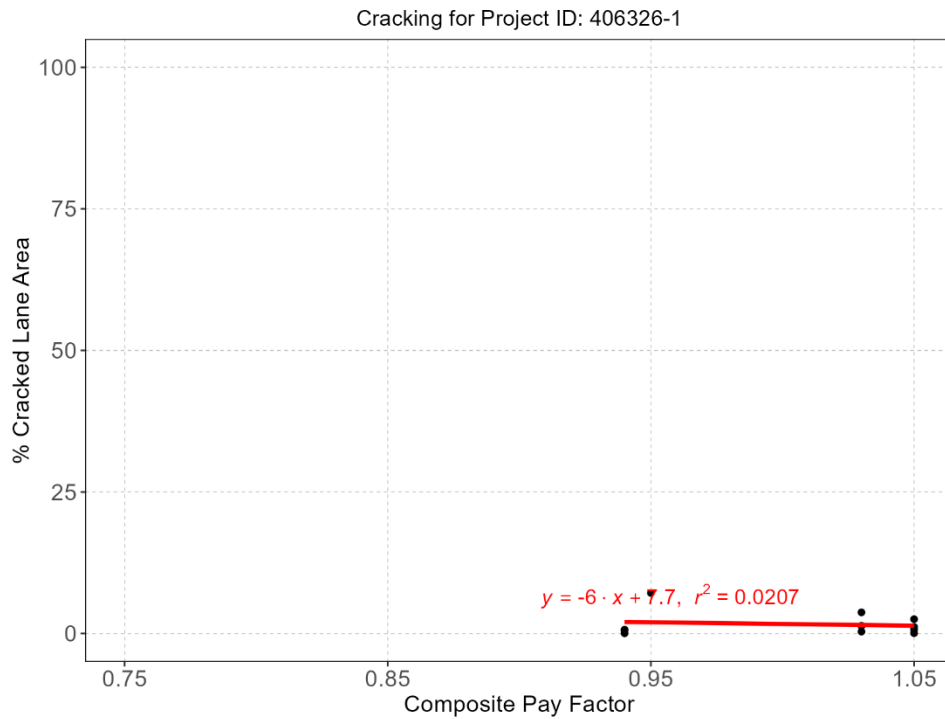


Figure 22. Example Cracking vs CPF Trend for Open Graded Mixture (Project 406326-1).

It is noted that these trends were not foreseen before all the distress data was gathered and compiled. It is also noted that there are two major factors that are responsible for such poor correlation between PF and performance data at the project level. These factors are:

1. **Small number of samples (i.e., data points) per project**: In order to derive an empirical relationship (e.g., regression) between CPF and pavement distress data, it is necessary to have sufficient number of data points for each relationship to be established. However, the number of data points available for PF versus distress ranged from 2 to 26 points per project, and averaged 9 data points per project, which is considered insufficient for establishing an empirical relationship.
2. **Minimal distresses (i.e., insufficient range of distresses)**: As discussed previously, most of the LOTs (and sublots) compiled in the comprehensive database only showed minimal distress. In order to establish an empirical relationship using statistical methods, it is also important that both the independent variable (e.g., CPF) and the dependent variable (e.g., cracking) span a wide range. However, most of the sublots were still performing very well (after 13+ years of service), which translates to minimal distress and a relatively narrow range for the distress data (especially at the project level).

Due to the above data related challenges, it is concluded that the project level analysis is not feasible with the data that is available in the comprehensive database. As such, the project level analysis has not been pursued further for this study.

4.2. NETWORK LEVEL ANALYSIS

Since the project level analysis did not provide any useful results due to the small number of data points and relatively narrow range of observed distress, the analysis has been repeated at the network¹ level. In other words, the traditional statistical methods (such as regression and ANOVA) were used to analyze all of the CPF and distress data included in the comprehensive database without dividing them into any subsets (or projects).

As examples of the network level analyses, Figure 23 and Figure 24 show the relationships between CPF and total cracking, for dense and open graded mixtures, respectively. These figures also include the linear regression lines that were fitted to the respective data sets.

Although these figures show a relatively wide range of CPF from 0.80 to 1.05 (Note that any LOTs with CPF less than 0.75 should have been removed and replaced per FDOT's acceptance specification), the majority of the data points are located towards the x-axis (i.e., no cracking) and causing the regression line to be established near the x-axis with a flat slope. Similar to the project level analysis, these figures clearly show that the correlation between CPF and total cracking was poor at best ($R^2 \ll 0.1$).

¹ The term "network" herein is defined as the projects, LOTs, and sublots that have been made available for this study (i.e., those included in the comprehensive database). It should NOT be regarded as the entire "roadway network" maintained by FDOT.

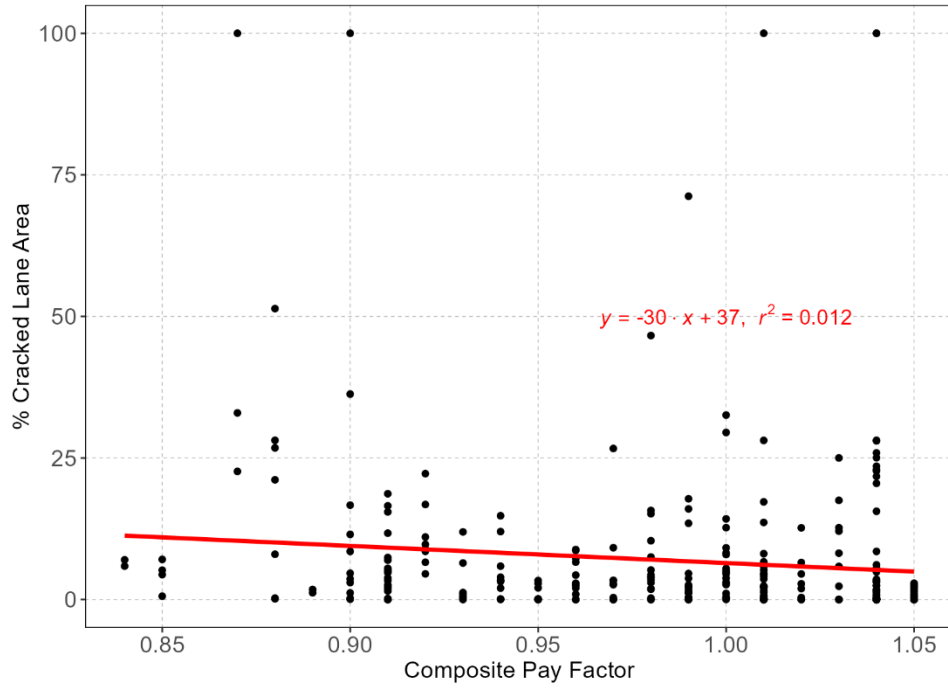


Figure 23. Network Level Cracking vs CPF Trend for Dense Graded Mixtures.

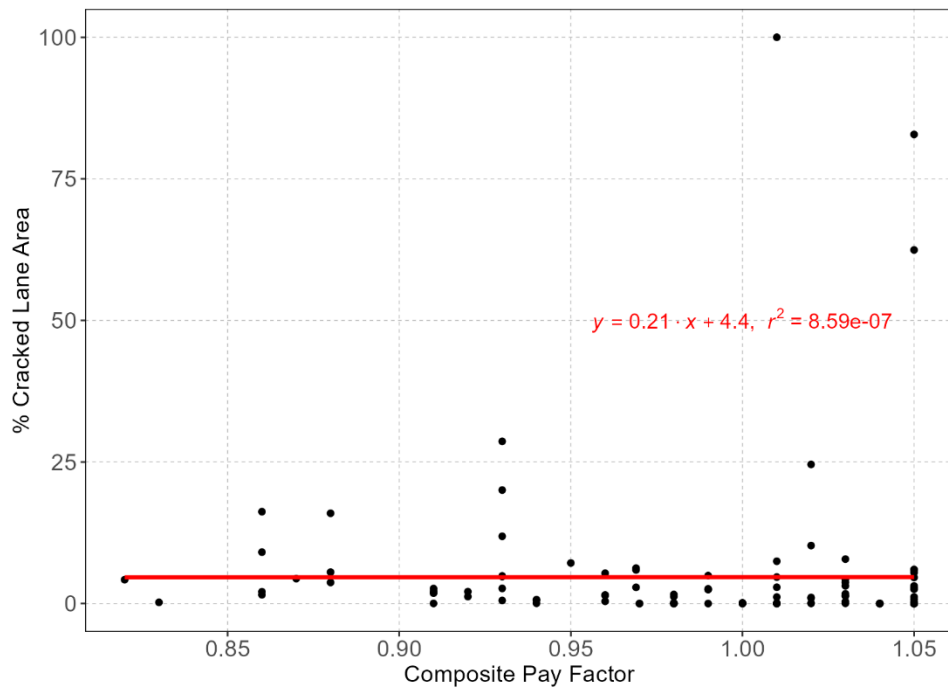


Figure 24. Network Level Cracking vs CPF Trend for Open Graded Mixtures.

Since the challenge seemed to stem from insufficient range of distresses, it was questioned if the good performing LOTs (and sublots) were subjected to lower traffic and/or thicker AC than those showing higher levels of distress. As such, it was also attempted to normalize the distress with respect to some of these external variables.

Figure 25 and Figure 26 show the relationship between CPF and total cracking normalized by ADTT for dense and open graded mixtures, respectively. Again, both these figures show very poor correlation.

In addition, it was also of interest to determine if one or more of the external factors (i.e., those that are not related to the quality of the mixture as determined by PF) such as ADTT was interfering with the PF vs. performance relationship. As such, the relationship between ADTT and the observed distresses were also examined without considering PF. These correlations are provided in Figure 27 and Figure 28 for dense and open graded mixtures, respectively. Clearly, these correlations were just as poor.

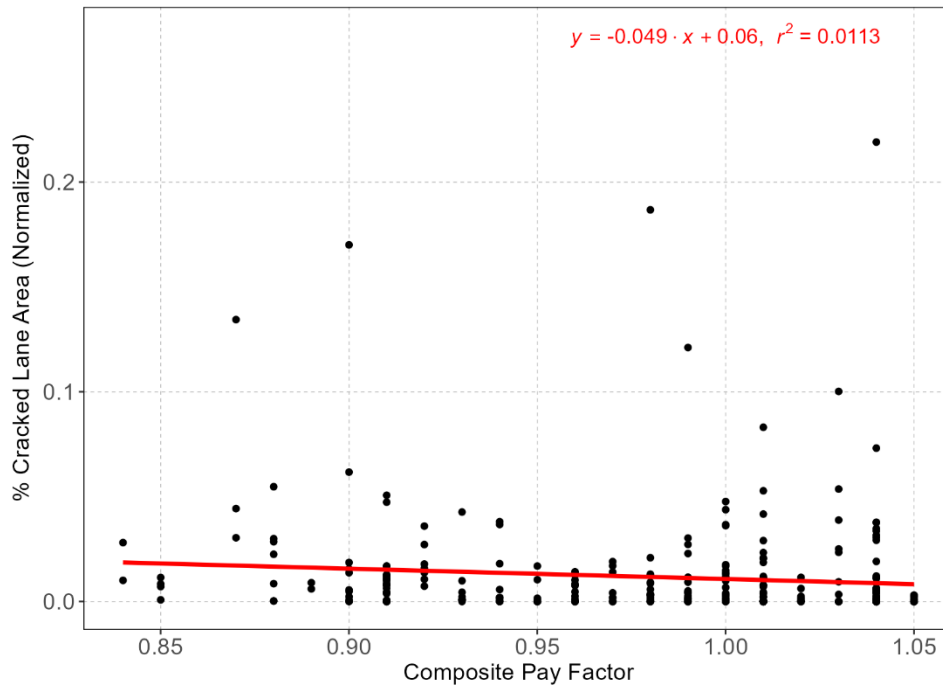


Figure 25. Network Level Cracking (Normalized by ADTT) vs CPF Trend for Dense Graded Mixtures.

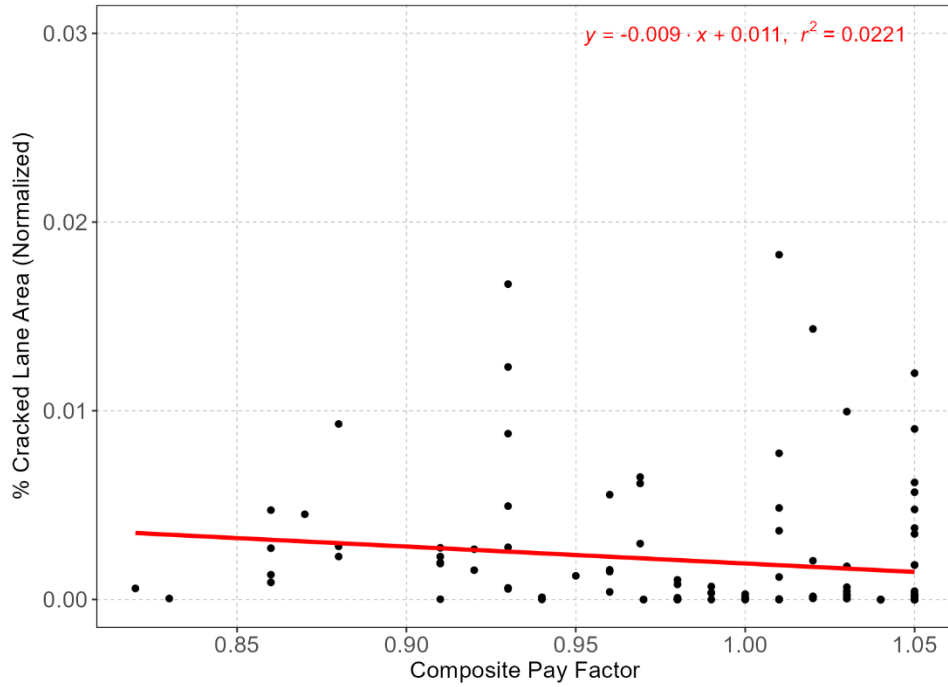


Figure 26. Network Level Cracking (Normalized by ADTT) vs CPF Trend for Open Graded Mixtures.

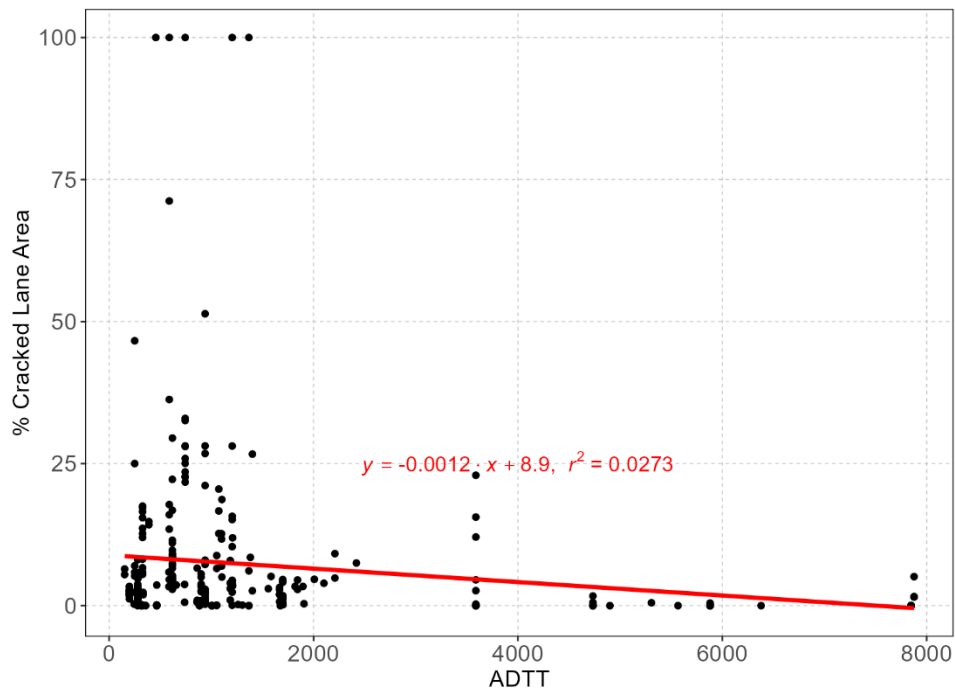


Figure 27. Network Level Cracking vs ADTT Trend for Dense Graded Mixtures.

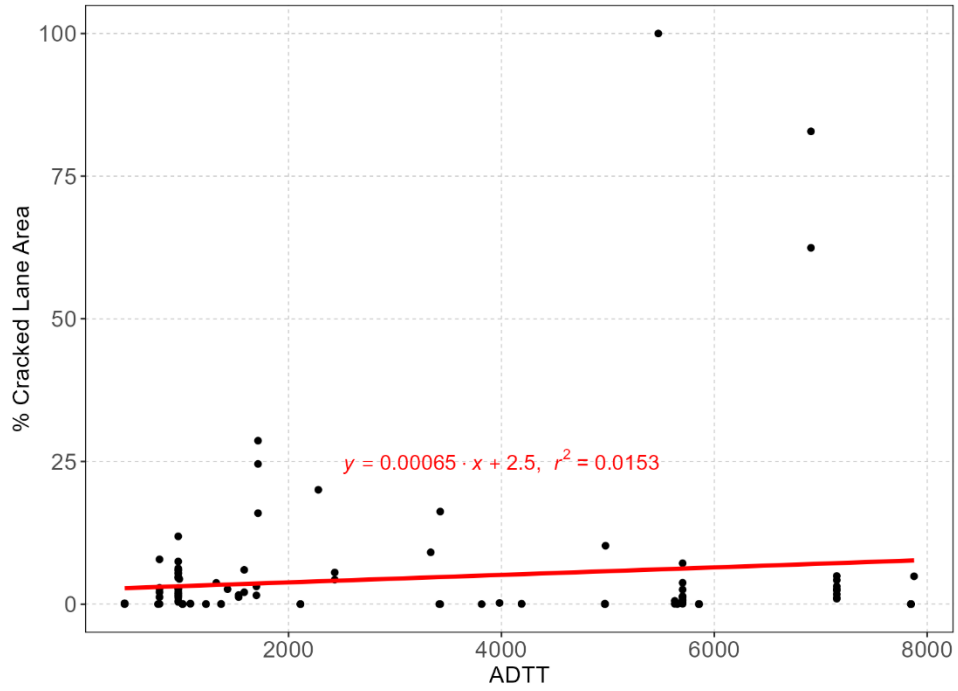


Figure 28. Network Level Cracking vs ADTT Trend for Open Graded Mixtures.

5. LOGISTIC REGRESSION FOR NETWORK LEVEL ANALYSIS

As seen from the previous chapter, the traditional regression methods were not able to provide any useful insight into the relationship between PF and pavement performance data. Recall that the primary challenges with the gathered data include (1) insufficient amount of data and (2) minimal distresses observed from the selected pavement sections.

To overcome the challenges mentioned above, a Multinomial Logistic Regression Analysis (MLRA) was performed. One of the primary differences between the traditional statistical methods (e.g., regression and ANOVA) and MLRA is that the response variable (i.e., the dependent variable which is the distress) is modeled as a continuous variable in conventional regression or ANOVA, while it is modeled as a categorical variable in MLRA.

The primary advantage of treating the response variable as a categorical variable is that it can distinguish the sublots with minimal amount of distresses in a more strict manner. For example, in the traditional statistical methods that treat the response variable as a continuous variable, a subplot with 1.0 percent cracking versus another subplot with 3.0 percent cracking may not be of significant difference in developing the overall trend (See Figure 23 as an example). However, if the cracking categories are established such that the above sublots (one with 1.0 percent cracking and the other with 3.0 percent cracking) fall into two distinct categories, they are treated as, or enforced to be, two sublots with completely distinct cracking performance.

This chapter of the report documents the efforts related to MLRA analyses and presents the relevant results.

5.1. MULTINOMIAL LOGISTIC REGRESSION FOR CRACKING

For cracking, the available sublots were assigned to one of the following categories, based on the total amount of surface cracking.

1. None to Minimal: Cracks in total lane area < 2.0 percent
2. Low: 2.0 percent \leq Cracks in total lane area < 5.0 percent
3. Medium: 5.0 percent \leq Cracks in total lane area < 10.0 percent
4. High: 10.0 percent \leq Cracks in total lane area < 20.0 percent
5. Very High: Cracks in total lane area \geq 20.0 percent

Although it is well agreed that cracking (especially top-down cracking) is the predominant distress for FDOT's roadways (Roque et. al., 2004), most of the sublots included in this study only showed minimal cracking. Therefore, the above categories were established to better distinguish the amount of cracking, especially for those with less than 10 percent cracking.

Table 16 and Table 17 summarize the p-values obtained from cracking MLRA for dense and open graded mixtures, respectively. These p-values indicate whether the PF obtained from a certain category (e.g., "Low" cracking category) is significantly different from the PF of a "reference category" (which was set to be the "None to Minimal" category). As an example,

Table 16 indicates that the CPF values from Medium and High cracking categories were significantly different from those of “None to Minimal” category.

Based on the significance level of 0.05, Table 16 indicates that for dense graded mixtures, all PF values except for the binder content, were found to be significant for one or more cracking categories. Similarly, Table 17 indicates that only the CPF and the No. 4 Sieve (PF_P4) were found to be significant for certain cracking categories of open graded mixtures. In general, these p-values do not show a clear trend and are somewhat inconsistent, which may be attributed to the lack of data, especially in the cracking categories of “Medium” through “Very High”.

Table 16. Summary of p-values from Cracking Logistic Analysis (Dense Graded)

Pay Factor	Cracking Category			
	Low	Medium	High	Very High
Composite Pay Factor (CPF)	0.062	0.000	0.014	0.053
Roadway Density (% G _{mm}) (PF_Density)	0.002	0.000	0.005	0.139
Percent Air Voids (PF_Va)	0.630	0.892	0.577	0.009
Asphalt Binder Content (PF_Pb)	0.068	0.094	0.988	0.772
Percent Passing No. 8 Sieve (PF_P8)	0.133	0.210	0.274	0.000
Percent Passing No. 200 Sieve (PF_P200)	0.049	0.969	0.145	0.010

Note 1: Highlighted cells indicate statistically significant variables (p-value < 0.05)

Table 17. Summary of p-values from Cracking Logistic Analysis (Open Graded)

Pay Factor	Cracking Category			
	Low	Medium	High	Very High
Composite Pay Factor (CPF)	0.010	0.152	0.011	0.774
Asphalt Binder Content (PF_Pb)	0.837	0.778	0.165	0.266
Percent Passing 3/8 Inch Sieve (PF_P3.8)	0.607	0.653	0.730	0.581
Percent Passing No. 4 Sieve (PF_P4)	0.016	0.007	0.534	0.546
Percent Passing No. 8 Sieve (PF_P8)	0.919	0.222	0.066	0.391

Note 1: Highlighted cells indicate statistically significant variables (p-value < 0.05)

To better understand the effect of different PF values, the MLRA results were used to generate the probabilities of a pavement section falling into the respective cracking categories in terms of PF. These results are provided in Appendix H for dense graded mixtures and in Appendix I for open graded mixtures.

An example of such result is provided in Figure 29, which shows the probabilities of a subplot falling into the respective cracking categories as a function of CPF for dense graded mixtures. This figure reveals clear trends for the “None to Minimal” and “Medium” cracking categories. On the other hand, the other categories are relatively flat without a clear trend, likely due to the lack of data points within each category.

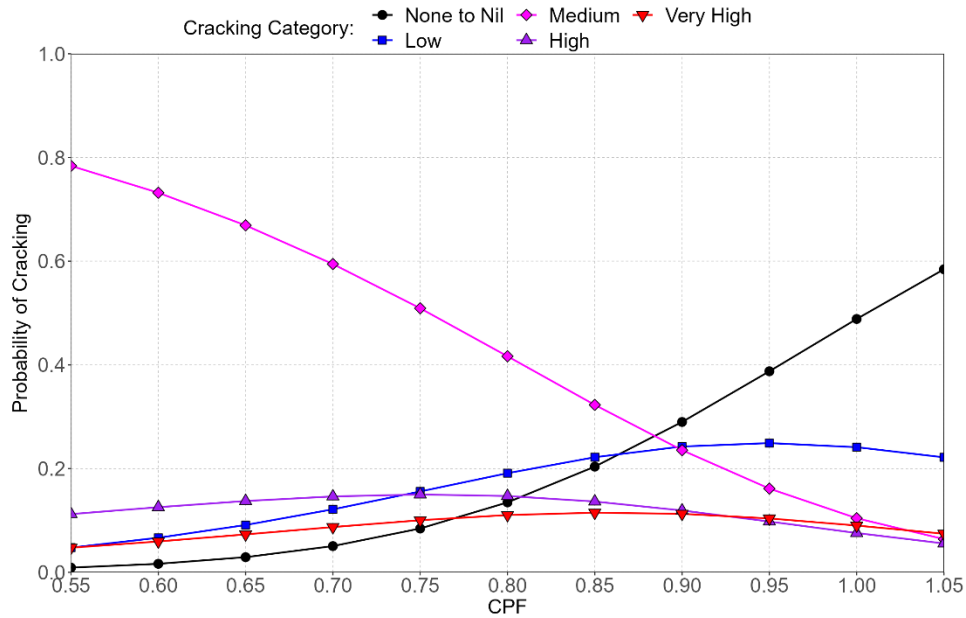


Figure 29. Probability of Cracking Category vs. CPF for Dense Graded Mixtures.

In general, the logistic analysis requires sufficient number of samples in each category (i.e., Low, Medium, High, and Very High cracking categories in this case) to be able to provide reliable results. To overcome the issue of insufficient number of data points in each cracking category, the MLRA results are summarized in terms of the following combined probabilities in the following:

1. **None to Low:** Combined probability of a subplot falling into “None to Minimal” or “Low” cracking category (i.e., less than 5 percent total cracking).
2. **Medium to Very High:** Combined probability of a subplot falling into “Medium”, “High”, or “Very High” cracking category (i.e., more than 5 percent total cracking).

Figure 30 shows the predicted probabilities for the latter combined category of “Medium to Very High” (i.e., >5% Cracking) for dense graded mixtures. The figure clearly shows that except for PF_P200, all PF values have a positive impact on cracking (i.e., the higher the PF, the lower the probability of cracking). Moreover, the figure shows that the effect of CPF is the most significant, followed by No. 8 Sieve (PF_P8), Air Voids (PF_Va), density (PF_Density), and binder content (PF_Pb).

Although the No. 200 Sieve (PF_P200) was found to be statistically significant (Table 16) for very high amount of cracking, its trend shown in Figure 30 is somewhat reversed (i.e., the higher the PF_P200, the higher the probability of cracking). It is possible that the issue of insufficient number of data points may not have been resolved by combing the categories. Nevertheless, the effect of PF_P200 is relatively minimal, compared to the other PF values.

Similarly, Figure 31 shows the predicted probabilities for the “Medium to Very High” cracking category for open graded mixtures. Except for the 3/8” Sieve (PF_P3.8), all PF values are showing a positive impact (higher PF corresponding to lower cracking), with the effect of CPF

being most significant. On the other hand, the No. 8 Sieve (PF_P8), No. 4 Sieve (PF_P4), and binder content (PF_Pb) showed relatively similar impact, especially in the PF range between 0.75 and 1.05.

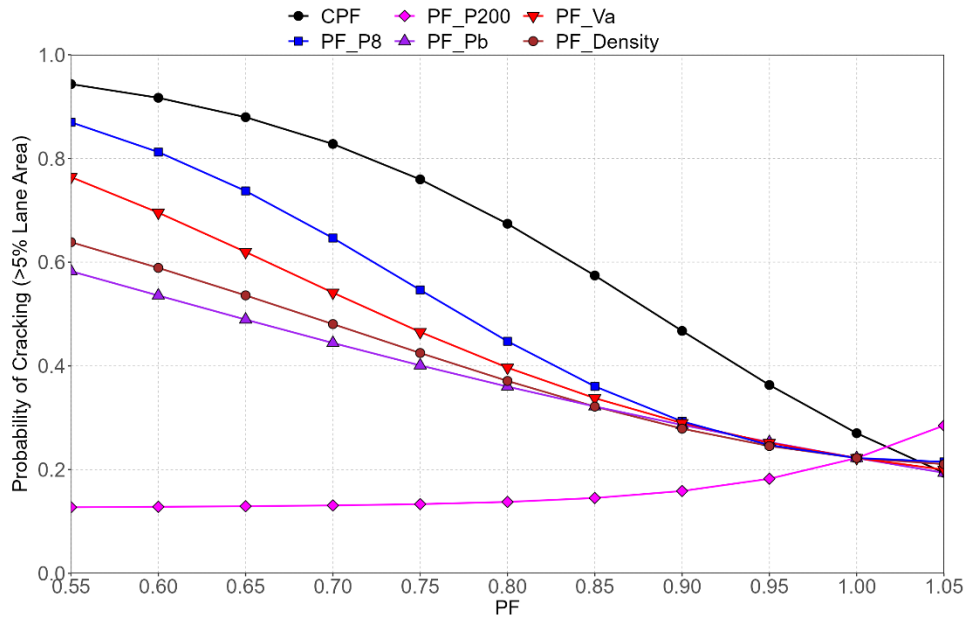


Figure 30. Logistic Regression Predicted Cracking Probability for Dense Graded Mixtures.

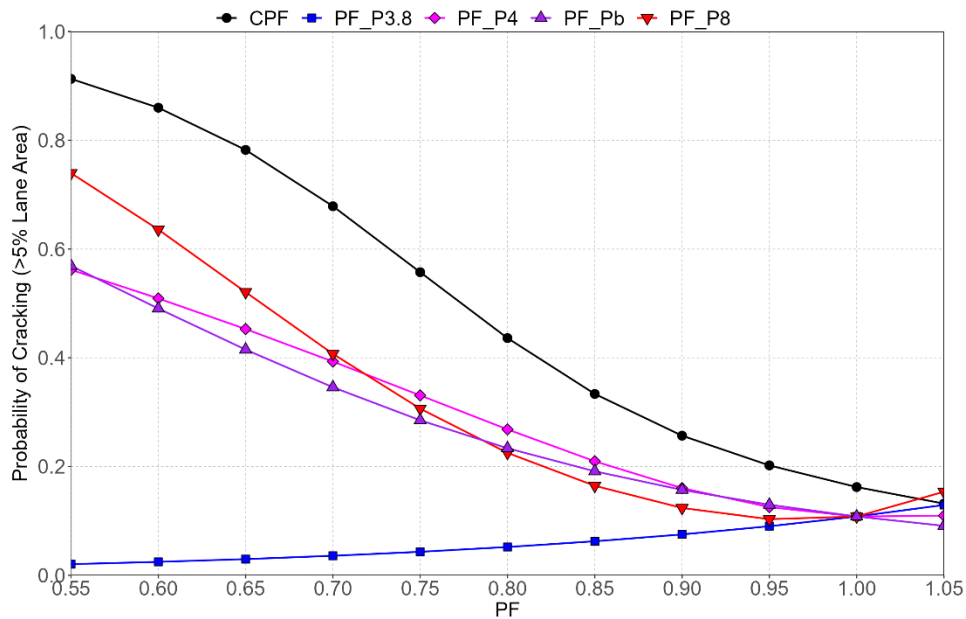


Figure 31. Logistic Regression Predicted Cracking Probability for Open Graded Mixtures.

5.2. MULTINOMIAL LOGISTIC REGRESSION FOR RUTTING

For rutting, the sublots were initially assigned to the following categories, based on measured rut depth.

1. None to Minimal: Rut depth < 0.10 in.
2. Low: 0.10 in. ≤ Rut depth < 0.20 in.
3. Medium: 0.20 in. ≤ Rut depth < 0.30 in.
4. High: 0.30 in. ≤ Rut depth < 0.40 in.
5. Very High: Rut depth ≥ 0.40 in.

Table 18 and Table 19 summarize the rutting p-values from MLRA for dense and open graded mixtures, respectively. These tables indicate that except for No. 8 Sieve (PF_P8) for dense graded mixtures and No. 4 Sieve (PF_P4) for open graded mixtures, the PF values were generally found to be statistically insignificant.

Table 18. Summary of p-values from Rutting Logistic Analysis (Dense Graded)

Pay Factor	Rutting Category			
	Low	Medium	High	Very High
Composite Pay Factor (CPF)	0.099	0.959	0.202	0.157
Roadway Density (% G _{mm}) (PF_Density)	0.380	0.213	0.114	0.296
Percent Air Voids (PF_Va)	0.328	0.739	0.338	0.589
Asphalt Binder Content (PF_Pb)	0.122	0.597	0.246	0.635
Percent Passing No. 8 Sieve (PF_P8)	0.077	0.000	0.002	0.138
Percent Passing No. 200 Sieve (PF_P200)	0.172	0.527	0.277	0.687

Note 1: Highlighted cells indicate statistically significant variables (p-value < 0.05)

Table 19. Summary of p-values from Rutting Logistic Analysis (Open Graded)

Pay Factor	Rutting Category			
	Low	Medium	High	Very High
Composite Pay Factor (CPF)	0.188	0.579	0.295	NA
Asphalt Binder Content (PF_Pb)	0.119	0.960	0.090	NA
Percent Passing 3/8 Inch Sieve (PF_P3.8)	0.762	0.927	0.325	NA
Percent Passing No. 4 Sieve (PF_P4)	0.027	0.220	0.718	NA
Percent Passing No. 8 Sieve (PF_P8)	0.864	0.364	0.117	NA

Note 1: NA indicates insufficient number of sublots

Note 2: Highlighted cells indicate statistically significant variables (p-value < 0.05)

Similar to the cracking analysis presented earlier, the MLRA results were used to generate the probabilities of a subplot falling into the respective rutting categories in terms of PF. These results are provided in Appendices J and K for dense and open graded mixtures, respectively.

In the following, the MLRA results are summarized in terms of the following combined probabilities:

1. **None to Minimal**: This category has not been combined with other categories and remained on its own, because over 50 percent of the sublots already belonged to this category. As such, this category still represents the probability of a subplot showing less than 0.10 in. rutting
2. **Low to Very High**: Combined probability of a subplot falling into “Low”, “Medium”, “High” or “Very High” rutting category (i.e., more than 0.10 in. rutting)

Figure 32 and Figure 33 show the probabilities for “Low to Very High” rutting category (i.e., rut depth greater than 0.1 in.) for dense and open graded mixtures, respectively. Both these figures show that CPF is not the most significant factor that relates to rut depth. More specifically, the No. 8 Sieve (PF_P8) is found to be the most significant for dense graded mixtures, followed by CPF, No. 200 Sieve (PF_P200), and binder content (PF_Pb). For open graded mixtures, the binder content (PF_Pb) showed the most significant effect, followed by the 3/8” Sieve (PF_P3.8) and CPF.

Figure 32 also indicates that rutting of dense graded mixtures is not sensitive to density (PF_Density) and air voids (PF_Va), as seen from the flat slope from these curves. In addition, Figure 33 shows that the trends for No. 4 Sieve (PF_P4) and No. 8 Sieve (PF_P8) are reversed for open graded mixtures.

It is noted that the probabilities of rutting shown in Figure 32 and Figure 33 are generally high. For example, the probability of rutting from a dense graded mixture is close to 50 percent even when the highest PF value of 1.05 is achieved. However, this should not be confused with “severe” or “excess” rutting. It is reminded that the probabilities shown in these graphs are for the rut depth being greater than 0.1 in. and not necessarily the probabilities corresponding to very severe rut depths. In addition, as previously shown in Figure 17, the majority of the sublots exhibited less than 0.2 in. rutting after 13+ years of service. The fact that these sublots are only showing minimal rut is in agreement with FDOT’s past experience: rutting is not the most predominant distress for flexible pavements in Florida.

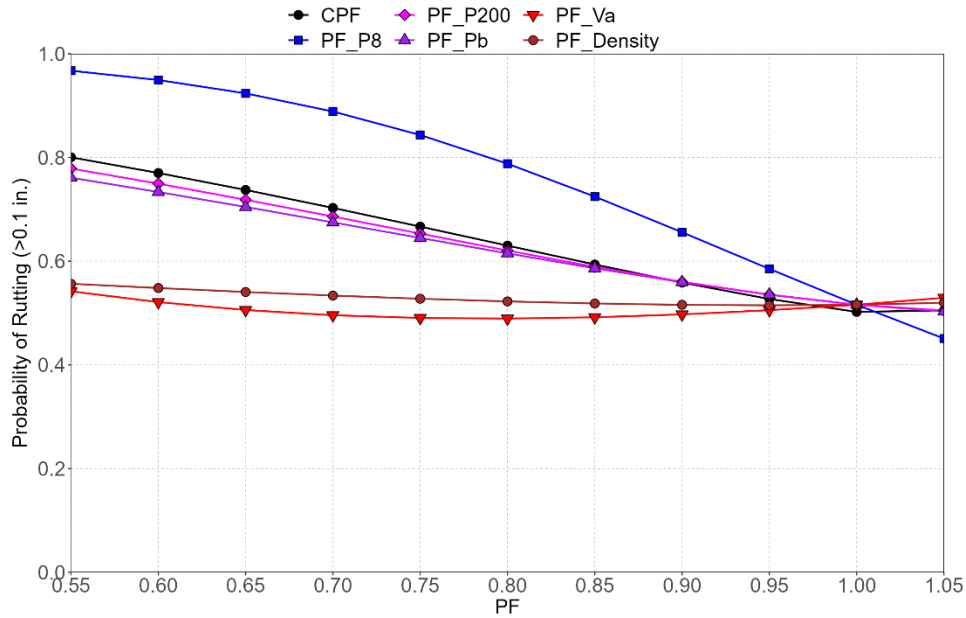


Figure 32. Logistic Regression Predicted Rutting Probability for Dense Graded Mixtures.

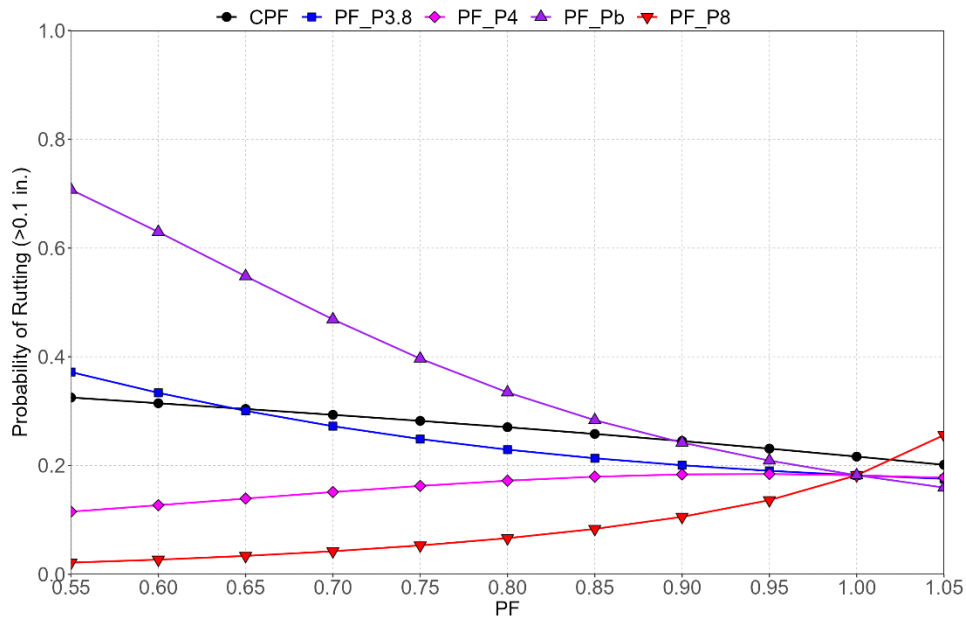


Figure 33. Logistic Regression Predicted Rutting Probability for Open Graded Mixtures.

5.3. MULTINOMIAL LOGISTIC REGRESSION FOR RAVELING

For raveling, the sublots were assigned to one of the following categories, as defined by the LCMS analysis library discussed previously.

1. No Raveling: $RI < 200$
2. Low (or Light) Raveling: $200 \leq RI \leq 290$

3. Medium (or Moderate) $290 < RI \leq 475$
4. High (or Severe) Raveling: $RI > 475$

Table 20 and Table 21 summarize the raveling p-values obtained from MLRA for dense and open graded mixtures, respectively. Note that the CPF and binder content (PF_Pb) are found to be statistically significant for both dense and open graded mixtures. For open graded mixtures, the No. 8 Sieve was also found to be significant.

Table 20. Summary of p-values from Raveling Logistic Analysis (Dense Graded)

Pay Factor	Raveling Category		
	Low	Medium	High
Composite Pay Factor (CPF)	0.037	0.410	0.015
Roadway Density (% G _{mm}) (PF_Density)	0.172	0.370	0.692
Percent Air Voids (PF_Va)	0.916	0.877	0.197
Asphalt Binder Content (PF_Pb)	0.104	0.884	0.001
Percent Passing No. 8 Sieve (PF_P8)	0.617	0.923	0.629
Percent Passing No. 200 Sieve (PF_P200)	0.535	0.834	0.184

Note 1: Highlighted cells indicate statistically significant variables (p-value < 0.05)

Table 21. Summary of p-values from Raveling Logistic Analysis (Open Graded)

Pay Factor	Raveling Category		
	Low	Medium	High
Composite Pay Factor (CPF)	0.617	0.005	0.787
Asphalt Binder Content (PF_Pb)	0.797	0.007	0.437
Percent Passing 3/8 Inch Sieve (PF_P3.8)	0.176	0.095	0.532
Percent Passing No. 4 Sieve (PF_P4)	0.373	0.084	0.096
Percent Passing No. 8 Sieve (PF_P8)	0.767	0.158	0.005

Note 1: Highlighted cells indicate statistically significant variables (p-value < 0.05)

The MLRA was used again to generate the probabilities of a subplot falling into the respective raveling categories. These results are provided in Appendices L and M for dense and open graded mixtures, respectively.

In the following, the MLRA results are summarized in terms of the following combined probabilities:

1. **None to Low:** Combined probability of a subplot falling into “No raveling” or “Light” raveling category (i.e., $RI \leq 290$)
2. **Medium to High:** Combined probability of a subplot falling into “Medium” or “High” raveling category (i.e., $RI > 290$)

Figure 34 and Figure 35 show the probabilities for “Medium to High” raveling obtained for dense and open graded mixtures, respectively. Clearly, both these figures show that the effect of

CPF is most pronounced for raveling of both dense and open graded mixtures. Also note that the binder content (PF_Pb) has a significant impact on both dense and open graded mixtures. In addition, the No. 8 Sieve (PF_P8) is also found to have a significant impact on open graded mixtures, which is consistent with the p-values presented in the above tables.

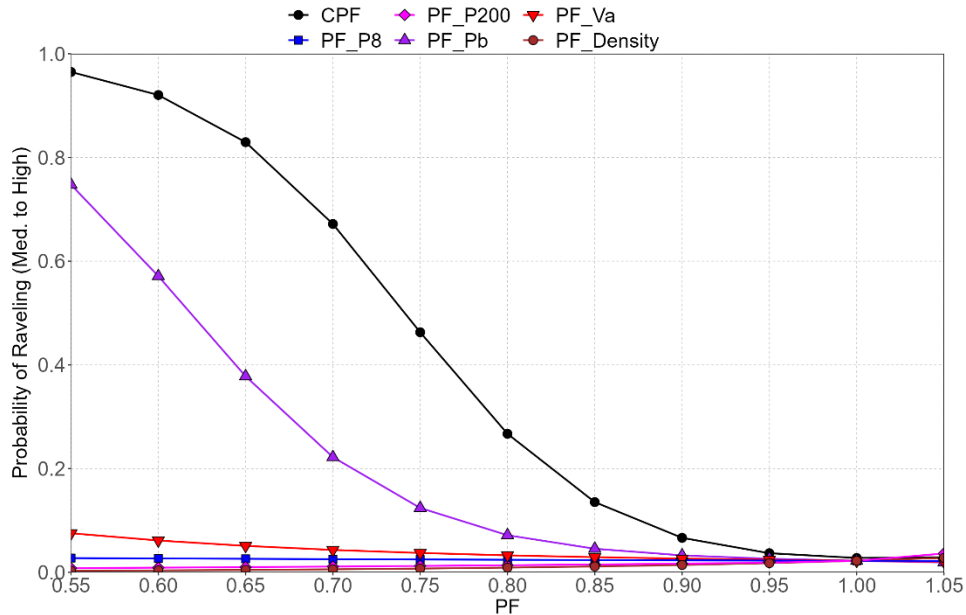


Figure 34. Logistic Regression Predicted Raveling Probability for Dense Graded Mixtures.

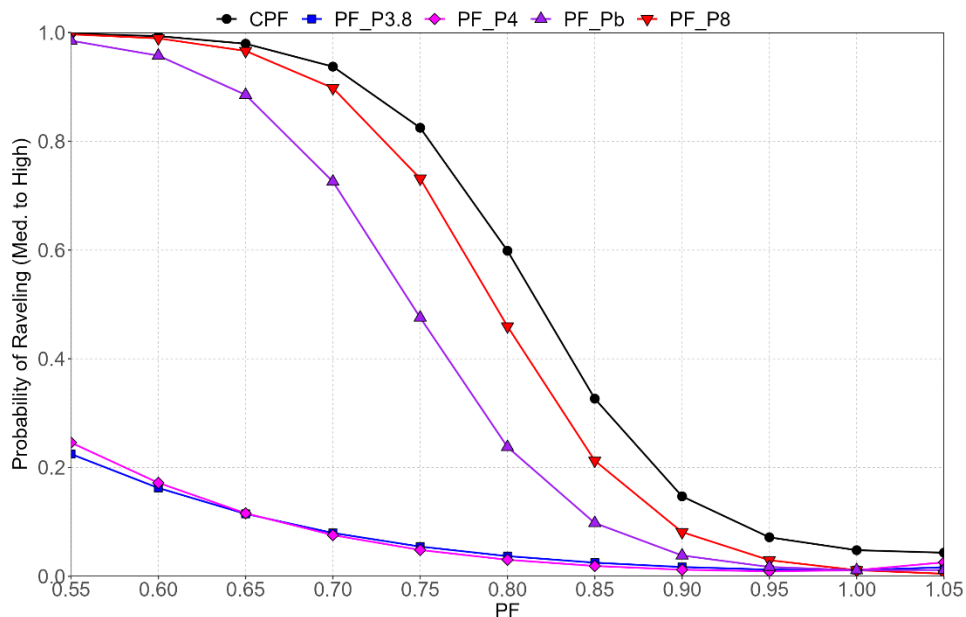


Figure 35. Logistic Regression Predicted Raveling Probability for Open Graded Mixtures.

5.4. LOGISTIC ANALYSIS SUMMARY AND DISCUSSION

As a summary of the probabilities obtained from logistic analyses, Figure 36 shows the probabilities of “higher level” of cracking (cracked area > 5%), rutting (rut depth > 0.1 in), and raveling (RI >290) as functions of CPF for dense graded mixtures. Similarly, Figure 37 shows the corresponding probabilities for open graded mixtures.

It should be noted that the range of CPF in the comprehensive database was limited to between 0.8 and 1.05 for both mixtures (again, FDOT’s specification indicates that any LOT with CPF below 0.75 should be removed and replaced). As such, although these figures show the probabilities for CPF ranging from 0.55 to 1.05, the highlighted areas of CPF less than 0.8 did not have any data points (i.e., the probability curves were extrapolated accordingly, based on the S-shaped logistic function fitted over the available data for CPF greater than or equal to 0.80).

Without considering the region of extrapolation, these figures generally show that CPF has a profound effect on cracking of both dense and open graded mixtures. On the other hand, the effect of CPF on rutting is relatively minimal (as seen by the flat slope). As discussed previously, although the rutting probabilities are generally higher than other distresses, the rut depth considered herein is fairly minimal (0.1 in.). These figures also show that when the CPF is relatively high (i.e., > 0.9 for dense and > 0.95 for open), the probability of raveling is mostly below 10 percent. However, when the CPF drops below 0.85, the probability of raveling increases significantly.

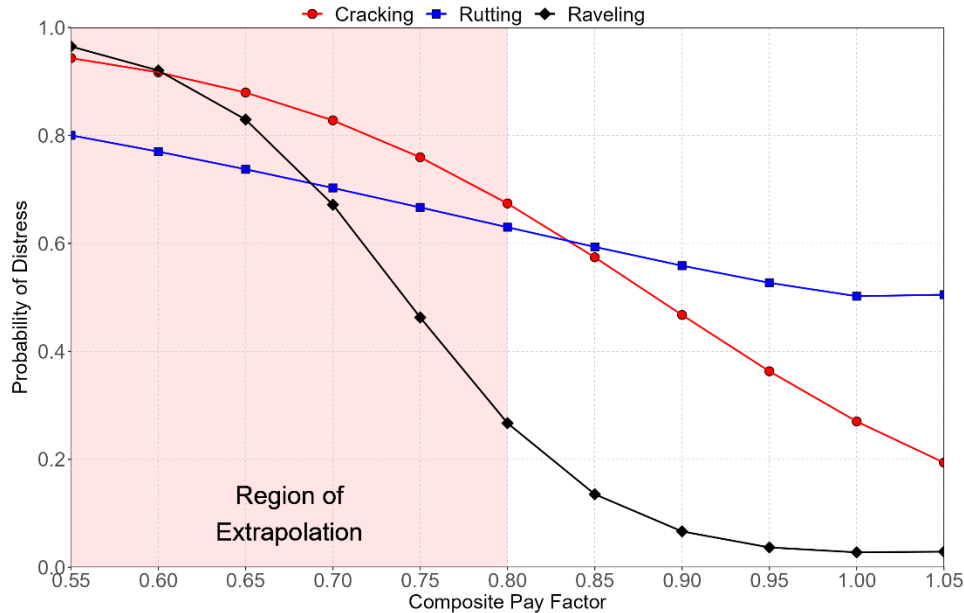


Figure 36. Summary of Logistic Regression Predicted Probabilities for Dense Graded Mixtures.

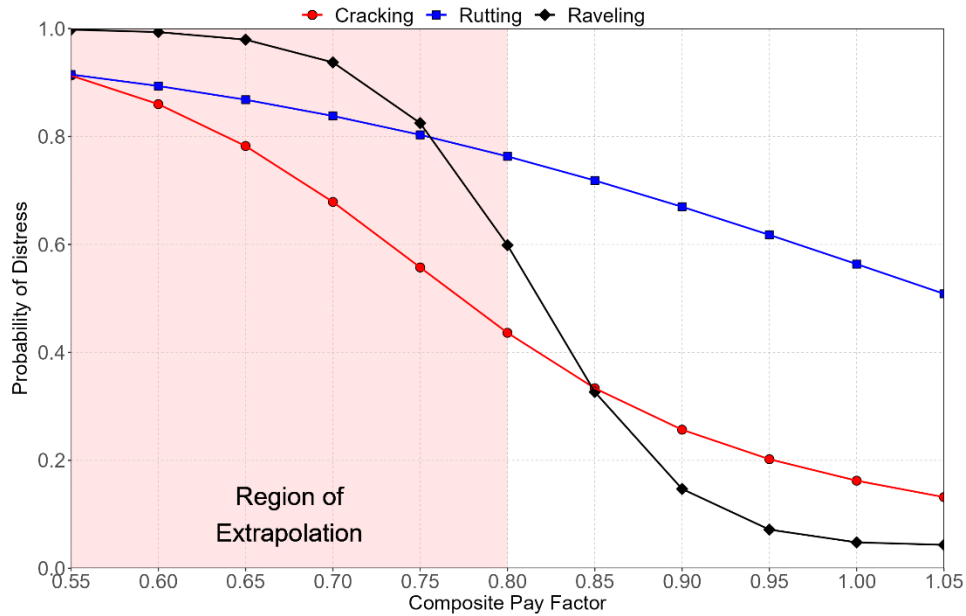


Figure 37. Summary of Logistic Regression Predicted Probabilities for Open Graded Mixtures.

Although the MLRA analysis provided more reasonable and interesting results than the conventional statistical methods such as regression, it is not without limitations. The following summarizes the limitations of MLRA, as related to the results shown previously.

1. One of the primary assumptions that had been made for MLRA is that the PF values are sufficient to represent the “Quality of the Mixture” (in terms of their respective AQC’s such as density) which is the focus of this study and is the only factor assumed to have an impact on measured distress.

In other words, it was assumed that the mixtures and the pavement structures were designed adequately for the site condition (e.g., traffic, foundation, etc.): no mixtures or structures were over-designed (which may cause minimal distress) or under-designed (which may cause excess distress). While it is possible that the external factors such as pavement foundation may have contributed to higher (or lower) levels of distress, the effect of these external variables cannot be assessed using MLRA conducted herein.

2. The distress data included in this study were obtained from in-service pavements that had been in place for 13+ years with very good performance. Therefore, the probabilities shown in Figure 29 through Figure 37 are considered valid only for the pavements (or sublots) that survived approximately 13 (±1) years.

The consequent limitation of such limited data and hence, the presented probabilities is that it is not possible to make inferences regarding the pavement life. In other words, the effect of CPF on pavement service life and the PFs (or AQC’s) that are important for ensuring extended pavement life (or preventing premature failure) cannot be assessed using the above analysis.

3. Although MLRA generally requires a large number of samples in each defined category, the analysis still suffered from lack of data, especially in the categories corresponding to higher levels of distress. Although combining some of these categories may have helped in identifying a trend in the data, some of the calculated probabilities still showed no trend (i.e., flat) while some others showed trends that are counterintuitive.
4. Although the PF values can range from 0.55 to 1.05 in theory, most of the PF values gathered in the comprehensive database ranged from 0.80 to 1.05. As such, the probabilities corresponding to PF values below 0.80 (Figure 29 through Figure 37) were mostly developed as a result of extrapolation. Therefore, these probabilities should not be taken for granted, and interpreted with caution.

6. DEVELOPMENT OF RECOMMENDATIONS

In the previous chapter of this report, a Multinomial Logistic Regression Analysis (MLRA) was conducted to assess the impact of FDOT's Percent Within Limits (PWL) specifications on long-term performance of asphalt pavements. The purpose of this chapter is to carry out additional simulations using the MLRA methodology, and to develop recommendations that can be implemented by FDOT for improving the PWL specification.

6.1. SUMMARY OF LOGISTIC REGRESSION

Recall that a unique characteristic of the MLRA is that the response variables (e.g., cracking and rutting) are treated as categorical variables. Initially, the distresses were categorized into four or five categories depending on their amount or severity. Then for each distress, some of the categories were merged to yield two final distress categories: One category to represent minimal or no distress, and the other category to represent higher levels of distress. For the purpose of this chapter, the focus is given to the latter category defined as the following.

3. **“Medium to Very High” Cracking**: This category was established by combining “Medium”, “High”, and “Very High” cracking categories, and represents those with more than 5 percent total cracking (in terms of lane area).
4. **“Low to Very High” Rutting**: This category was established by combining “Low”, “Medium”, “High”, and “Very High” rutting categories, and represents those with rut depths greater than 0.10 in.
5. **“Medium to High” Raveling**: This category was established by combining “Medium” and “High” raveling categories, and represents those with Raveling Index (RI) greater than 290.

6.2. LOGISTIC SIMULATION

As reviewed in Chapter 1, the CPF is simply a weighted average of the individual Pay Factor (PF) values that are obtained for different Acceptance Quality Characteristics (AQC). During FDOT's initial implementation of the Percent Within Limits (PWL) specification in 2002, the weights for the respective AQCs were determined based on the perceived impact they have on the constructed pavement (or material) performance. Since then, the AQC weights for the dense graded mixtures have been updated in the July 2019 edition of FDOT's specification, while those of the open graded mixtures have not experienced any updates.

Figure 36 and Figure 37 clearly showed that the CPF (and hence the AQC weights) determined by FDOT is cost-effective, i.e., the higher the CPF the lower the probability of distress. However, it is possible that one may get a different set of probability curves if a new set of weights are used for computing the CPF. Moreover, the data used for generating the probability curves of dense graded mixtures (Figure 36) were collected from pavements that are 13 (± 1) years old, i.e., the CPF values in Figure 36 were obtained based on the weights in FDOT's 2002 specification and do not reflect the updates implemented in 2019.

As such, the goal of the additional logistic simulation is to determine if the weights implemented in FDOT's current specification is effective, and/or to determine if there is a better set of weights that can be explored.

6.2.1. Assumptions and Limitations

Due to the lack of data available for the MLRA analyses, a number of assumptions had to be made for the logistic analysis which, in turn, led to several limitations. Note that these assumptions and limitations (discussed in the previous chapter) are also applicable to the logistic simulations conducted herein. As such, the assumptions and limitations deemed particularly important for the additional simulations are briefly summarized in the following.

1. It is assumed that the distresses (i.e., cracking, rutting, and raveling) are only dependent on the quality of the mixture represented by the PF value of the respective AQC's. In other words, the effect of other external site conditions (e.g., traffic, foundation) or inappropriate designs (i.e., over-designed or under-designed pavements) are not considered in the analysis.
2. It is also assumed that FDOT's existing AQC's are adequate for assessing the quality of the mixture, i.e., introduction of a new AQC cannot be considered herein and is beyond the scope of the logistic analysis.
3. The logistic analysis and the resulting probability curves are only applicable to pavements that have been in service for 12 to 14 years, i.e., the logistic analysis cannot address any issues related to pavement service life (e.g., premature failures). This is primarily because the distress survey for this study was conducted on in-service pavements of age 12 to 14 years.
4. Most of the PF and CPF values made available for this study ranged from 0.80 to 1.05. As such, although the PF can range from 0.55 to 1.05 in theory, the probability curves generated for the PF values below 0.80 (as shown in Figure 36 and Figure 37) are mostly an outcome of extrapolating the probability curves.

Given the above assumptions and limitations, the scope of the additional logistic analysis was confined to investigating the effect of AQC weights. The following section describes the scenarios (i.e., different set of weights) used in the simulation.

6.2.2. Simulation Scenarios

Table 22 lists the AQC's of dense graded mixtures and their weights used in the logistic simulation. Note that the simulation ID No. 0 corresponds to the weights initially implemented in FDOT's 2002 specification, and is regarded as the baseline scenario. Starting from this baseline scenario, the simulation sequences 1 through 20 were generated by reducing the weight of a given AQC (e.g., PF-P8) by 5 percent and increasing the weight of a different AQC (e.g.,

PF_P200) by the same amount (such that the sum of all weights remain 100). It is also noted that the simulation ID No. 12 corresponds to the weights that have been updated in the 2019 edition of FDOT’s specification.

Table 22. Weights of AQC’s Simulated in Logistic Analysis (Dense Graded Mixtures)

Simul. ID	Weights (Percent)				
	Percent Passing No. 8 Sieve (PF_P8)	Percent Passing No. 200 Sieve (PF_P200)	Asphalt Binder Content (PF_Pb)	Percent Air Voids (PF_Va)	Roadway Density (% Gmm) (PF_Density)
0*	5	10	25	25	35
1	0	15	25	25	35
2	0	10	30	25	35
3	0	10	25	30	35
4	0	10	25	25	40
5	10	5	25	25	35
6	5	5	30	25	35
7	5	5	25	30	35
8	5	5	25	25	40
9	10	10	20	25	35
10	5	15	20	25	35
11	5	10	20	30	35
12**	5	10	20	25	40
13	10	10	25	20	35
14	5	15	25	20	35
15	5	10	30	20	35
16	5	10	25	20	40
17	10	10	25	25	30
18	5	15	25	25	30
19	5	10	30	25	30
20	5	10	25	30	30

Note* : Simulation ID No. 0 corresponds to the original weights implemented in FDOT’s 2002 specification.

Note** : Simulation ID No.12 corresponds to the new weights implemented in FDOT’s 2019 specification.

Similarly, Table 23 lists the AQC’s of open graded mixtures and their weights. Again, simulation ID No. 0 serves as the baseline scenario and corresponds to the weights implemented in FDOT’s specification since 2002. The scenarios 1 through 12 were generated by reducing the weight of one AQC by 5 percent and adding it to a different AQC.

Table 23. Weights of AQC's Simulated in Logistic Analysis (Open Graded)

Simul. ID	Weights (Percent)			
	Percent Passing 3/8 Inch Sieve (PF P3.8)	Percent Passing No. 4 Sieve (PF P4)	Percent Passing No. 8 Sieve (PF P8)	Asphalt Binder Content (PF Pb)
0*	20	30	10	40
1	15	35	10	40
2	15	30	15	40
3	15	30	10	45
4	25	25	10	40
5	20	25	15	40
6	20	25	10	45
7	25	30	5	40
8	20	35	5	40
9	20	30	5	45
10	25	30	10	35
11	20	35	10	35
12	20	30	15	35

Note* : Simulation ID No. 0 corresponds to the original weights implemented in FDOT's 2002 specification.

6.3. LOGISTIC SIMULATION RESULTS

6.3.1. Dense Graded Mixtures

For each of the scenarios developed in Table 22, the CPF was recalculated using the new weights, and the probability curve was regenerated using the logistic analysis methodology. Appendices N, O, and P provide the individual probability curves generated for cracking, rutting, and raveling of dense graded mixtures, respectively.

As a summary, Figure 38 shows the range of all cracking probability curves generated using the weights in Table 22 for dense graded mixtures. The figure also shows the baseline probability curve (i.e., the original weights or simulation ID No. 0) corresponding to the weights in FDOT's 2002 specification, along with the curve for simulation ID No. 12 which represents FDOT's new weights implemented in 2019 for dense graded mixtures.

Figure 38 clearly indicates that compared to FDOT's original weights, the new weights implemented in 2019 reduces the probability of cracking for CPF values above 0.80 as well as in the extrapolated region (i.e., CPF < 0.80). In fact, the CPF generated from the new weights (simulation ID No. 12) coincides with the lower limit of the probability range shown in Figure 38. In other words, the new weights exhibited the lowest probability of cracking amongst the scenarios shown in Table 22.

Similarly, Figure 39 and Figure 40 show the range of probabilities obtained for rutting and raveling of dense graded mixtures, respectively. Figure 39 shows that the new weights exhibit

lower rutting probability than the original weights, although it is not the one with the lowest rutting probability. On the other hand, Figure 40 shows that the new weights significantly reduce the probability of raveling, and the new weights coincide with the probability curve of lowest raveling probability.

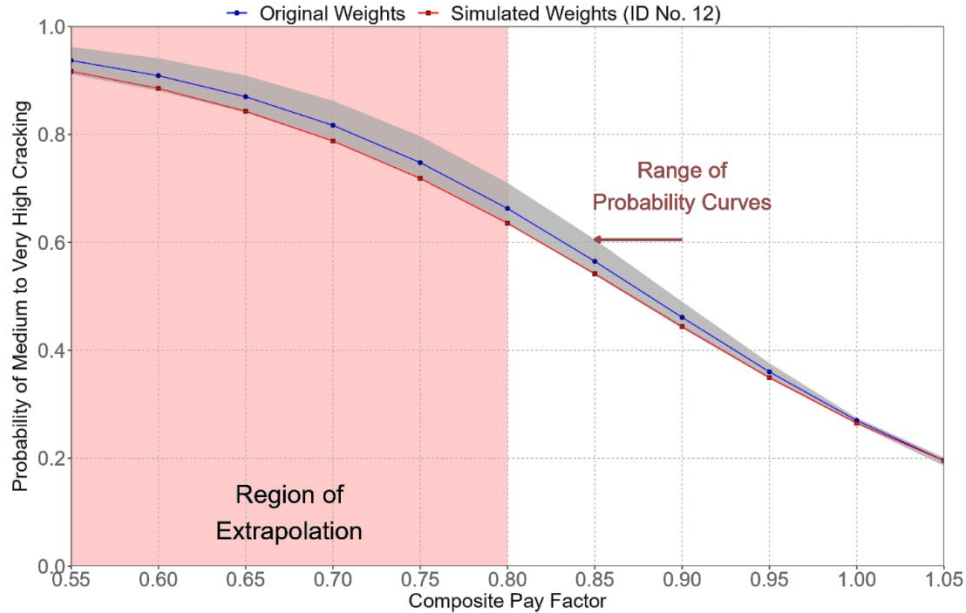


Figure 38. Simulated Probability Curves for Dense Graded Mixture Cracking (Simulation ID 0 vs. 12).

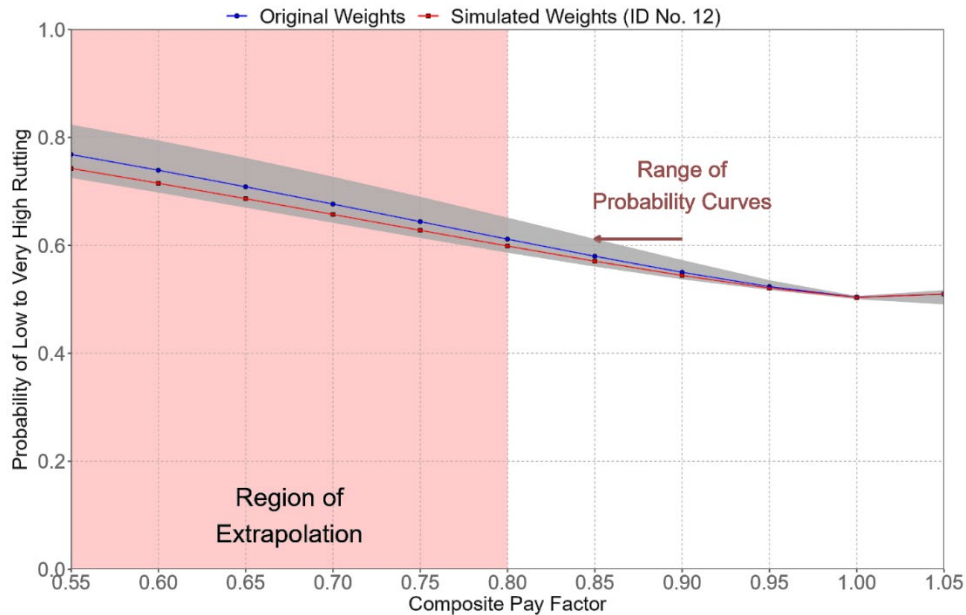


Figure 39. Simulated Probability Curves for Dense Graded Mixture Rutting (Simulation ID 0 vs. 12).

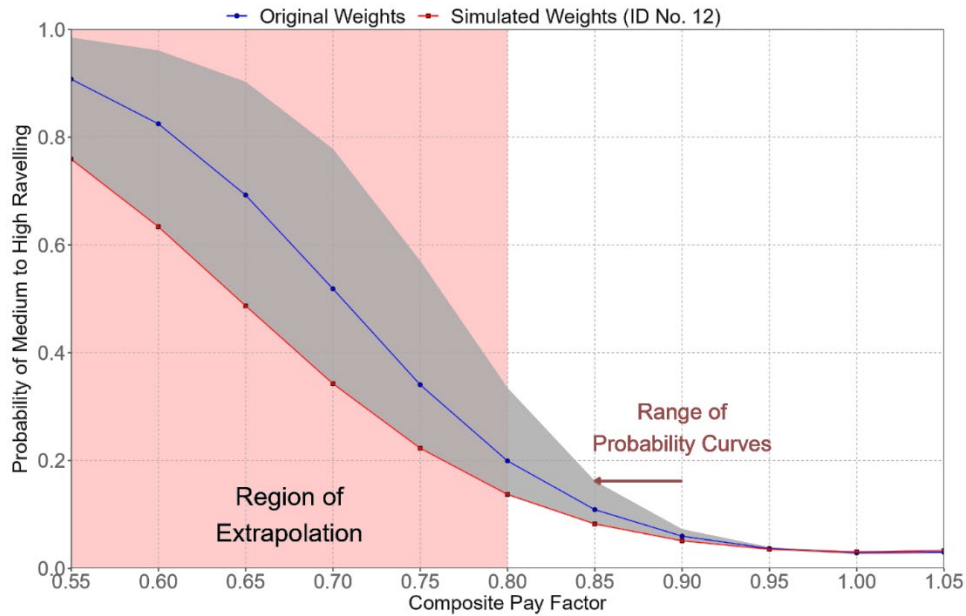


Figure 40. Simulated Probability Curves for Dense Graded Mixture Raveling (Simulation ID 0 vs. 12).

As indicated by the above results, FDOT’s new weights implemented in 2019 reduce the probability of long-term cracking and raveling significantly, and may offer higher potential for improved pavement performance compared to the original weights in the 2002 specification.

Although the new weights did not correspond to the one with lowest probability of rutting, the new weights did show a reduced probability for rutting, compared to the original weights. It is emphasized again that rutting is not the predominant distress for FDOT’s pavements. Furthermore, the rut depth considered herein is minimal (0.1 in.) for pavements of age 12 to 14 years.

6.3.2. Open Graded Mixtures

Similar to the dense graded mixtures, the logistic analysis was conducted for open graded mixtures with the scenarios shown in Table 23. Appendices Q, R, and S provide the individual probability curves generated from the logistic simulations for cracking, rutting, and raveling, respectively.

Figure 41, Figure 42, and Figure 43 provide summaries of the logistic simulations for cracking, rutting, and raveling, respectively. These figures show the range of probability curves for the respective distresses, along with the curves corresponding to simulation ID No. 0 (i.e., the current weights in FDOT’s specification). Also shown in these figures is the probability curves from simulation ID No. 7. Compared to the baseline scenario, this particular case represents the following changes in the AQC weights.

1. Twenty-five (25) percent weight for Percent Passing 3/8 Inch Sieve (PF_P3.8) which is a 5 percent increase from the current weight of 20 percent.
2. Five (5) percent weight for Percent Passing No. 8 Sieve (PF_P8) which is a 5 percent reduction from the current weight of 10 percent.
3. Thirty (30) percent weight for Percent Passing No. 4 Sieve (PF_P4) which remains unchanged.
4. Forty (40) percent weight for Asphalt Binder Content (PF_Pb) which also remains unchanged.

Simulation ID No. 7 with the weights described above was specifically chosen because it showed the lowest probabilities for both cracking (Figure 41) and raveling (Figure 43), although the probability of rutting did not show much improvement (Figure 42). Again, since rutting is not the primary mode of failure for FDOT's pavements and the range of rutting considered herein is minimal (i.e., approximately 0.1 in), this is not considered to be a significant concern.

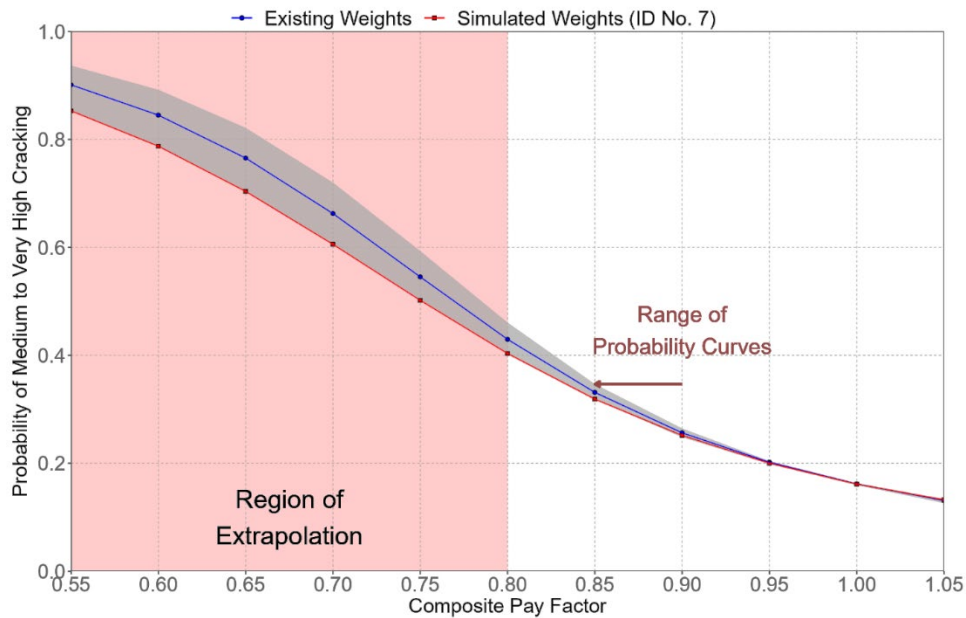


Figure 41. Simulated Probability Curves for Open Graded Mixture Cracking (Simulation ID 0 vs. 7).

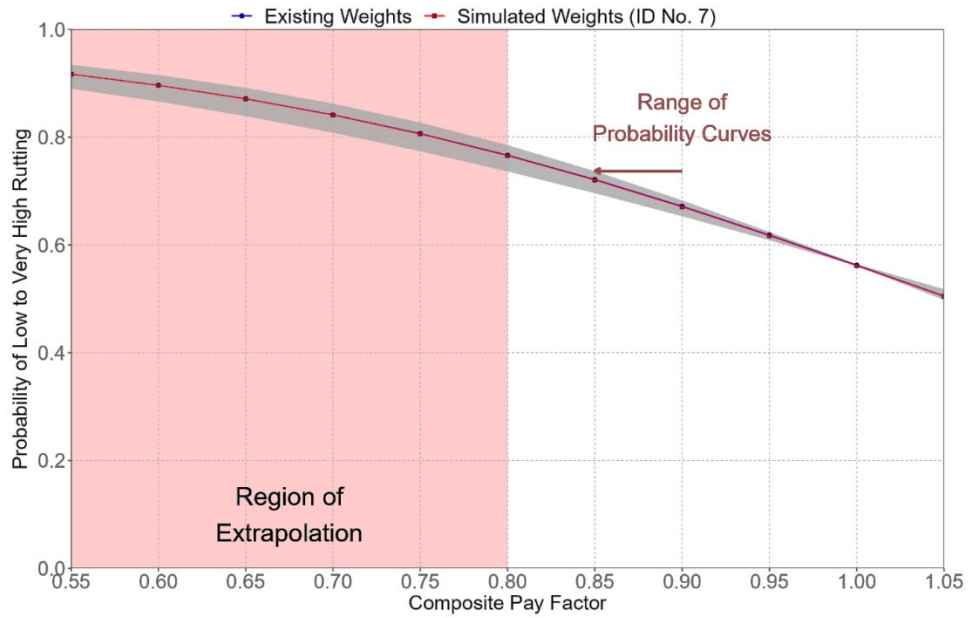


Figure 42. Simulated Probability Curves for Open Graded Mixture Rutting (Simulation ID 0 vs. 7).

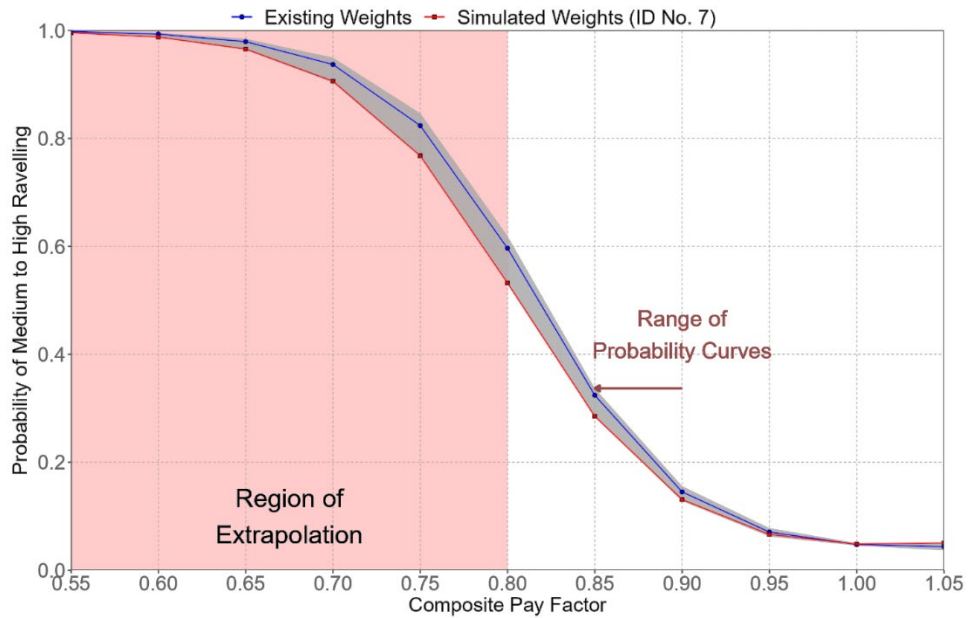


Figure 43. Simulated Probability Curves for Open Graded Mixture Raveling (Simulation ID 0 vs. 7).

6.4. SUMMARY OF RECOMMENDATIONS

In this chapter, the logistic regression methodology was used to run additional simulations using the available data in an attempt to provide recommendations that can be implemented by FDOT for improving the PWL specification.

The additional logistic simulations were conducted for several scenarios that were generated by reducing the weight of a single AQC (e.g., PF-P8) by 5 percent and increasing the weight of a different AQC (e.g., PF_P200) by the same amount. Then the probability curves for cracking, rutting, and raveling were compared to the baseline scenario defined by the weights implemented in FDOT's 2002 PWL specification.

The results of the logistic simulation for dense graded mixtures indicated that FDOT's new weights implemented in their 2019 specification may reduce the probability of long-term cracking and raveling significantly compared to the original weights in the 2002 specification.

As for open graded mixtures, although FDOT's AQC weights implemented in 2002 (and still being used) are cost-effective, the logistic simulation revealed that there may be room for improvement. More specifically, the analysis showed that increasing the weight of Percent Passing 3/8 Inch Sieve (PF_P3.8) from 20 to 25 percent and decreasing the weight of Percent Passing No. 8 Sieve (PF_P8) from 10 to 5 percent may improve the long-term cracking and raveling performance of open graded mixtures.

Based on the above results obtained from the logistic analysis as well as the lessons learned from the course of this study, the following recommendations are provided for FDOT's future consideration.

1. For dense graded mixtures, it is recommended that FDOT continue to use the new weights implemented in 2019.
2. For open graded mixtures, it is recommended that FDOT explore the option of increasing the weight of PF_P3.8 by 5 percent and reducing the weight of PF_P8 by 5 percent, as suggested by the results of the logistic analysis. However, it is emphasized again that the logistic analysis was conducted on a limited number of data set. Therefore, implementation of the new weights (if deemed feasible) should be carried out slowly and presumably after further analysis of more recent data (e.g., using a shadow specification and/or a number of pilot projects).
3. One of the major limitations of the logistic analysis conducted for this study is that the results of the analysis could not be used to make useful inferences regarding the pavement service life. This is primarily because the distress data included in this study were obtained from pavements that were 12 to 14 years of age. As such, if a follow up study is deemed necessary, it is recommended that the pavement distress data be collected more frequently (e.g., every 2 or 3 years) for pavements with a wide range of performance (i.e., good vs. poor performing). It is believed that such a comprehensive data will allow for assessing the impact of FDOT's PWL specification on pavement

service life or at least on the rate of deterioration for each of the distresses to be considered.

7. SUMMARY AND CONCLUSIONS

FDOT's Percent Within Limits (PWL) specification for acceptance and payment of HMA materials was first implemented in 2002. One of the major differences between FDOT's new PWL specification and the old specification (which only had disincentives), is that the PWL system allows the contractors to earn incentives or disincentives depending on the quality of the materials and pavement they constructed. Since the implementation of the PWL specification in 2002, it has been refined several times based on research and feedback from industry as well as from FHWA before arriving at the current specification.

The basic premise of the incentive/disincentive specification based on the concept of PWL is that the long-term pavement performance is related to certain Acceptance Quality Characteristics (AQC's). However, such a relationship has not been defined or established based on FDOT's data. Due to the lack of such relationships, the quality characteristics and their weights currently implemented in FDOT's PWL specification were established empirically based on past experience and engineering judgement. As such, the primary objective of this study was to determine the level of impact that FDOT's PWL specification has on the long-term performance of asphalt pavements.

The review of literature as well as other agencies' specifications indicated that a majority of agencies have implemented PWL (or Percent Deficient, PD) for their acceptance specifications. Nonetheless, the AQC's as well as the weights used for calculating Composite Pay Factor (CPF) varied significantly among SHAs. Although FDOT's AQC's are commonly used by other agencies, the literature review did not reveal any evidence of an agency showing the relationship between these common AQC's (and weights) and long-term pavement performance.

A preliminary analysis conducted using the traditional statistical methods (e.g., regression) did not show good trends for FDOT's available data. Insufficient amount of data and minimal distresses observed from the selected pavement sections were identified as the primary challenges that are responsible for the poor correlations (i.e., $R^2 < 0.1$) observed during the preliminary analysis.

As an alternative to the traditional statistical methods that treat the response variable (i.e., distress) as a continuous variable, a Multinomial Logistic Regression Analysis (MLRA) was performed in which the response variables are treated as categorical variables. For this analysis, each distress (i.e., cracking, rutting, and raveling) was initially categorized into four to five categories depending on their amount or severity. Then, some of these categories were merged to yield two final categories (one category for almost no distress and the other for increased level of distress).

The MLRA results indicated that the Composite Pay Factor (CPF) determined by FDOT is cost-effective, in the sense that higher CPF values exhibited a lower probability of distresses. Moreover, it was shown that the CPF has a profound effect on cracking of both dense and open graded mixtures. On the other hand, the effect of CPF on rutting was minimal, which agrees with FDOT's past experience (i.e., rutting is not the predominant distress in Florida). The results also revealed that the probability of raveling can be kept to a minimum, if the CPF is higher than

0.85. However, if the CPF dropped below 0.85, the probability of raveling increased significantly.

The results of additional logistic simulation for dense graded mixtures indicated that FDOT's new weights implemented in their 2019 specification reduce the probability of long-term cracking and raveling significantly compared to the original weights in the 2002 specification. As such, it is recommended that FDOT continue to use the new AQC weights implemented in 2019.

As for open graded mixtures, although FDOT's AQC weights implemented in 2002 (and still being used) are cost-effective, the results indicated that the probabilities of cracking and raveling can be reduced further. Therefore, it is recommended that FDOT explore the option of increasing the weight of Percent Passing 3/8 Inch Sieve (PF_P3.8) by 5 percent and reducing the weight of Percent Passing No. 8 Sieve (PF_P8) by 5 percent, in accordance with the MLRA results.

8. REFERENCES

- Afferton, K.C., Freidenrich, J., and Weed, R.M. (1995). *Managing Quality: Time for a National Policy*, Transportation Research Record: Journal of the Transportation Research Board, No. 1340, pp. 3–39, Transportation Research Board, Washington, D.C.
- American Association of State Highway and Transportation Officials (AASHTO). (2018). *AASHTO R 9-05 Standard Practice for Acceptance Sampling Plans for Highway Construction*, AASHTO, Washington, D.C.
- American Association of State Highway and Transportation Officials (AASHTO). (2020). *AASHTO R 10-06 Standard Practice for Definition of Terms Related to Quality and Statistics as Used in Highway Construction*, AASHTO, Washington, D.C.
- American Association of State Highway and Transportation Officials (AASHTO). (2020). *AASHTO R 42-06 Standard Practice for Developing a Quality Assurance Plan for Hot-Mix Asphalt (HMA)*, AASHTO, Washington, D.C.
- American Association of State Highway and Transportation Officials (AASHTO). (1995). *Quality Assurance Guide Specification*, AASHTO, Washington, D.C.
- Bowery, F.J. Jr., and Hudson, S.B. (1976). *NCHRP Synthesis of Highway Practice 38: Statistically Oriented End-Result Specifications*, National Cooperative Highway Research Program, Transportation Research Board, National Research Council, Washington, D.C.
- Burati, J.L., Weed, R.M., Hughes, C.S., and Hill, H.S. (2003). *Optimal Procedures for Quality Assurance Specifications*, Report No. FHWA-RD-02-095, Office of Research, Development, and Technology, Federal Highway Administration, McLean, VA.
- Burati, J.L., Weed, R.M., Hughes, C.S., and Hill, H.S. (2004). *Evaluation of Procedures for Quality Assurance Specifications*, Report No. FHWA-HRT-04-046, Office of Research, Development, and Technology, Federal Highway Administration, McLean, VA.
- Code of Federal Regulations. (2020). §637.207 *Quality assurance program*, U.S. Government Publishing Office, Washington, D.C. Available online: https://www.ecfr.gov/cgi-bin/retrieveECFR?gp=1&SID=ccd236c4df946bd8434d988383aa4368&h=L&mc=true&n=sp23.1.637.b&r=SUBPART&ty=HTML#se23.1.637_1207, last accessed May 15, 2020.
- Coenen, A., Pforr, J.E., Hefel, S.A., and Paye, B.C. (2019). *State DOT Implementation of Statistical Analysis and Percent Within Limits*, Transportation Research Record: Journal of the Transportation Research Board, No. 2673 (2), pp. 583–592, Transportation Research Board, Washington, D.C.
- Duval, R. (2016). *FHWA Performance-Related Specifications for Asphalt Mixtures Asphalt Mix, Asphalt Mix ETG*, Fall River, Ma.

Elmore, W.E., Solaimanian, M. and Kennedy T. (1998). *Qualifying Items of Work for End-Result Specifications: Phases I and II*, Report No. FHWA/TX-99/1825-S, Texas Department of Transportation, Austin, TX.

Epps, J.A., Hand, A., Seeds, S., Schulz, T., Alavi, A., Ashmore, C., Monismith, C.L., Deacon, J.A., Harvey, J.T., and Leahy, R. (2002). *NCHRP Report 455: Recommended Performance-Related Specification for Hot-Mix Asphalt*, NCHRP Project No. D9-20, National Cooperative Highway Research Program, Transportation Research Board, National Research Council, Washington, D.C.

Federal Highway Administration (FHWA). (2007). *Highway Quality Compendium*, Federal Highway Administration, Washington, D.C.

Florida Department of Transportation (FDOT). (2000). *Standard Specifications for Road and Bridge Construction*. Florida Department of Transportation, Tallahassee, FL.

Florida Department of Transportation (FDOT). (2020). *Standard Specifications for Road and Bridge Construction*. Florida Department of Transportation, Tallahassee, FL.

Georgia Department of Transportation (GDOT). (2013). *Standard Specifications Construction of Transportation Systems*, Georgia Department of Transportation, Atlanta, GA.

Haider, S.W., Musunuru, G., and Chatti, K. (2017). *Why PWL is a better quality measure for developing PRS*, Bearing Capacity of Roads, Railways, and Airfields, Loizos. Et. al. ed. Athens, Greece.

Hand, A.J.T. and Epps, J.A. (2006). *Fundamentals of Percent Within Limits and Quality Control—Quality Assurance Compaction Specifications*, Transportation Research Circular Number E-C105, Transportation Research Board, National Research Council, Washington, D.C.

Hanna, A. , (2013). *NCHRP Research Results Digest 371: Quality-Related Pay Adjustment Factors for Pavements*, National Cooperative Highway Research Program, Transportation Research Board, National Research Council, Washington, D.C.

Hughes, C. S. (1995). *Results from VDOT's Pilot Project Using Volumetric Properties and Asphalt Content for Acceptance of Asphalt Concrete*, Virginia Transportation Research Council, Report No. VTRC 95-TAR9, Charlottesville, VA.

Hughes, C. S. (2005). *NCHRP Synthesis 346: State Construction Quality Assurance Programs*, National Cooperative Highway Research Program, Transportation Research Board, National Research Council, Washington, D.C.

Hughes, C.S., Moulthrop, J.S., Tayabji, S., Weed, R.M., and Burati, J.L. (2011). *Guidelines for Quality-Related Pay Adjustment Factors for Pavements, Final Report*, NCHRP Project No. 10-79, National Cooperative Highway Research Program, Transportation Research Board, National Research Council, Washington, D.C.

Mallick, R.B., Kandhal, P.S., Cooley, L.A., and Watson, D.E. (2000). *Design, Construction, and Performance of New-Generation Open-Graded Friction Courses*, Report No. NCAT 2000-01, National Center for Asphalt Technology (NCAT), Auburn, AL.

Maryland Department of Transportation (MDOT). (2019). *Standard Specifications for Construction and Materials*, Mississippi Department of Transportation, Annapolis, MD.

McCarthy, L.M., Callans, J., Quigley, R., and Scott, S.V. (2016). *NCHRP Synthesis 492 Performance Specifications for Asphalt Mixtures*, National Cooperative Highway Research Program, Transportation Research Board, National Research Council, Washington, D.C.

Merritt, D.K., Chang, G.K., and Rutledge, J.L. (2015). *Best Practices for Achieving and Measuring Pavement Smoothness, A Synthesis of State-of-Practice*, Report No. FHWA/LA.14/550, Louisiana Transportation Research Center, Baton Rouge, LA.

Mississippi Department of Transportation (MDOT). (2017). *Mississippi Standard Specifications for Road and Bridge Construction*, Mississippi Department of Transportation, Jackson, MS.

Moulthrop, J. and Witczak, M. (2011). *NCHRP Report 704: A Performance-Related Specification for Hot-Mixed Asphalt*, NCHRP Project No. D9-22, National Cooperative Highway Research Program, Transportation Research Board, National Research Council, Washington, D.C.

Moulthrop, J., James, M., Witczak, M., Jeong, M., McCarthy, L.M., and Mensching, D. (2012). *Evaluation of the Quality Related Specification Software (QRSS) Version 1.0 Preliminary Draft Final Report*, NCHRP Project No. 9-22 A, National Cooperative Highway Research Program, Transportation Research Board, National Research Council, Washington, D.C.

Nair, H., McGhee, K.K., Habib, A., Wells, M., and Saha, B. (2018). *Evaluation of Revised Incentive-Only Ride Specification for Asphalt Pavements*, Report No. FHWA/VTRC 18-R11, Virginia Department of Transportation, Richmond, VA.

Putman, B.J. (2012). *Evaluation of Open-Graded Friction Courses: Construction, Maintenance, and Performance*, Report No. FHWA-SC-12-04, South Carolina Department of Transportation, Columbia, SC.

Roque, R., Birgisson, B., Drakos, C., and Dietrich, B. Development and Field Evaluation of Energy-Based Criteria for Top-Down Cracking Performance of Hot Mix Asphalt. *Journal of Association of Asphalt Paving Technologists*, vol. 73, 2004.

Sebaaly, P.E., Schlierkamp, R., Diaz, C., Hajj, E., and Souliman, M. (2015). *Develop a PWL System for Dense Graded Hot Mix Asphalt Construction, Including Pay Factors*, Nevada Department of Transportation, Carson City, Nevada, NV.

Seneviratne, P.N. and David, S.T. (1996). *Performance of Open-Graded Surface Courses*, Report No. UT-94.07, Research and Development Division, Utah Department of Transportation, Salt Lake City, UT.

Sholar, G.A., Page, G.C., Musselman, J.A., Upshaw, P.B., and Moseley, H.L. (2005). *Development of the Florida Department of Transportation's Transportation's Percent Within Limits Hot-Mix Asphalt Specification*. Transportation Research Record: Journal of the Transportation Research Board, No. 1907, pp. 43–51, Transportation Research Board, Washington, D.C.

South Carolina Department of Transportation (SCDOT). (2007). *Standard Specifications for Highway Construction*, South Carolina Department of Transportation, Columbia, SC.

Stanard, C., Candaele, R., Charbeneau, R., and Barrett, M. (2007). *State of the Practice: Permeable Friction Courses*, Report No. FHWA/TX-08/0-5220-1, Texas Department of Transportation, Austin, TX.

Transportation Research Circular Number E-C235. (2018). *Glossary of Transportation Construction Quality Assurance Terms*, Transportation Research Board, National Research Council, Washington, D.C.

Utah Department of Transportation (UDOT). (2017). *Standard Specifications for Road and Bridge Construction*, South Carolina Department of Transportation, Salt Lake City, UT.

Wang, H., Wang, Z., Bennert, T., and Weed, R. (2015). *HMA Pay Adjustment*, Report No. FHWA NJ-2015-007, New Jersey Department of Transportation, Trenton, NJ.

Wang, H., Wang, Z., Bennert, T., and Weed, R. (2016). *Specification Limits and Pay Adjustment for Longitudinal Joint Density of Asphalt Pavements Case Study in New Jersey*, Transportation Research Record: Journal of the Transportation Research Board, No. 2573, pp. 98–106, Transportation Research Board, Washington, D.C.

Watson, D., Johnson, A., and Jared, D. (1998). *Georgia Department of Transportation's Progress in Open-Graded Friction Course Development*, Transportation Research Record: Journal of the Transportation Research Board, No. 1616, pp. 30–33, Transportation Research Board, Washington, D.C.

White, T.D. and Hillabrand, J.L. (2013). *Open Graded Friction Courses for HMA Pavements*, Report No. FHWA/MS-DOT-RD-13-207, Federal Highway Administration, Mississippi Department of Transportation.

White, T.D. and Ivy, J. (2009). *I-55 OGFC Field Permeability Testing*, Report No. FHWA/MS-DOT-RD-09-201, Federal Highway Administration, Mississippi Department of Transportation.
Willenbrock, J.H. and Kopac, P.A. (1977). *Development of Price-Adjustment Systems for Statistically Based Highway Construction Specifications*, Transportation Research Record:

Journal of the Transportation Research Board, No. 652, pp. 52–58, Transportation Research Board, Washington, D.C.

Zinke, S., Mahoney, J., Jackson, E., and Shaffer, G. (2008). *Comparison of the Use of Notched Wedge Joints vs. Traditional Butt Joints in Connecticut*, Report No. CT-2249-F-08-4, Connecticut Department of Transportation, Rocky Hill, CT.

APPENDIX A: REVIEW OF SHA PRACTICES

Table A.1 Summary of SHA Practices

States	Acceptance Quality Characteristics (AQC's)	Quality Measure	Pay Factors
Alabama	Air voids Asphalt content Gradation Mat density	Average deviation from a target value	The lowest pay factor in a LOT is applied to the contract price for the total tonnage in the LOT.
Alaska	Gradation Asphalt content Mat density	PWL	Two pay factors, Composite Pay Factor (CPF) including gradation and binder content and Density Pay Factor, are determined. Whichever is lower is then used for price adjustment for each individual LOT.
Arizona	Air voids Asphalt content Gradation Mat density	PWL	Two separate pay factors, mixture properties lot and compaction lot, are determined. The total unit price for any unit of accepted asphaltic concrete is the contract unit price, adjusted by the applicable mixture properties lot pay factor and compact ion lot pay factor. Mixture properties lot pay factor includes air voids, asphalt content, and gradation.
Arkansas	Air voids Asphalt content Voids in mineral aggregate Mat density	Average deviation from a target value	Price reductions are computed from the compliance limit for each property, and reductions for each property added together to obtain the total price reduction for the LOT. When the number of deviations for any property exceeds the maximum specified, or when the total price reduction for a lot is greater than 50%, that lot is not accepted. Incentives is included in the pay schedule for Binder course and/or surface Course.
California	Air voids Asphalt content Gradation Mat density	PWL	The composite quality factor used to determine the contractor's final payment adjustment on the lot is based on the contractors' verified quality-control test data for binder content, air voids, the Number 8 and Number 200 sieves, combined with the engineer's percent of maximum theoretical density determined from cores.
Colorado	Asphalt content Gradation Mat density	PWL	Designated formulas which are function of the PWL, called quality level (QL), and number of samples are used to calculate the pay factor for each quality characteristics. The Incentive or Disincentive Payment (I/DPs) values for each quality characteristics are then calculated and accumulated.

States	Acceptance Quality Characteristics (AQC's)	Quality Measure	Pay Factors
Connecticut	Asphalt content Gradation Mat density	Average deviation from a target value	Material (asphalt content and gradation) deficiency adjustment and density adjustment are separately applied to the contract price.
Delaware	Air voids Asphalt content Gradation Mat density	PWL	Payment is based on 70% weight for material production pay adjustment (composite PWL for air void, asphalt content, and gradation) and 30% weight for construction pay adjustment.
Florida	Air voids Asphalt content Gradation Mat density	PWL	For dense-graded HMA, Composite Pay Factor (CPF) with 0.40, 0.25, 0.20, 0.05, and 0.10 weight for density, air void, binder content, percent passing No. 8 sieve, and percent passing No. 200 sieve is determined. For open-graded HMA, Composite Pay Factor (CPF) with 0.40, 0.20, 0.30, and 0.10 weight for binder content, percent passing 3/8" sieve, percent passing No. 4 sieve, and percent passing No. 8 sieve is determined.
Georgia	Asphalt content Gradation Mat density	Average deviation from a target value	The mean of the deviations from the job mix formula of the tests in each LOT is determined by averaging the actual numeric value of the individual deviations from the job mix formula, disregarding whether the deviations are positive or negative amounts. When two or more pay factors for a specific lot are less than 1.0, the adjusted payment is determined by multiplying the contract unit price by the lowest pay factor. For the mat density, payment for each lot is calculated by multiplying the contract unit price by the adjusted pay factor.
Hawaii	Asphalt content Gradation Mat density	Average deviation from a target value	Agency approval for the mix design and density.
Idaho	Air voids Asphalt content Gradation Voids in mineral	PWL	A composite pay factor for mix aggregate, asphalt content, and density with different weights for different mixtures is determined.

States	Acceptance Quality Characteristics (AQC's)	Quality Measure	Pay Factors
	aggregate Mat density		
Illinois	Air voids Voids in mineral aggregate Mat density	PWL	A composite pay factor with 0.3, 0.3, and 0.4 weight for air void, VMA, and density is determined.
Indiana	Air voids Effective binder content Mat density	PWL	A composite pay factor with 0.30, 0.35, and 0.35 weight for air void, effective binder content, and density is determined for dense graded mixture. For open graded mixture, a composite pay factor with 0.20, 0.35, and 0.35 weight for effective binder content and air void is determined for open graded mixture.
Iowa	Air voids Film thickness Mat density	PWL	To determine the final payment, the unit price for the HMA bid item is multiplied by the pay factors for each quality characteristics.
Kansas	Air voids Mat density	PWL	Separate pay factors for the air void and density are determined.
Kentucky	Air voids Asphalt content Voids in mineral aggregate Mat density Joint density	Average deviation from a target value	For base and binder mixtures, a composite pay factor with 0.1, 0.25, 0.25, and 0.4 weight for binder content, air void, VMA, and mat density is determined. For surface mixture, a composite pay factor with 0.05, 0.25, 0.25, 0.3, and 0.15 weight for binder content, air void, VMA, mat density, and joint density is determined.
Louisiana	Theoretical maximum specific gravity (Gmm) Mat density	PWL	Adjustment factors for the theoretical maximum specific gravity (Gmm) is used for payment adjustment. Adjustments in contract unit price for mat density is then separately applied.
Maine	Air voids Asphalt content Voids in mineral	PWL	Four different methods are used for acceptance and determination of pay factor.

States	Acceptance Quality Characteristics (AQC's)	Quality Measure	Pay Factors
	aggregate Gradation Mat density		
Maryland	Air voids Mat density	PWL	A pay factor is calculated for both mat density and air voids. The lot pay factor is the higher of the two values when calculations for both mat density and air voids are 100 percent or higher. The lot pay factor is the product of the two values when only one of the calculations for either mat density or air voids is 100 percent or higher. The lot pay factor is the lower of the two values when calculations for both mat density and air voids are less than 100 percent.
Massachusetts	Air voids Asphalt content Mat density Thickness Ride quality	PWL	A composite pay factor with 0.10, 0.15, 0.35, 0.10, and 0.30 weight for asphalt content, air voids, density, thickness, and ride quality is determined.
Michigan	Air voids Asphalt content Voids in mineral aggregate Mat density	PWL	Overall Lot Pay Factor (OLPF) with 0.40, 0.30, 0.15, and 0.15 weight for density, air void, binder content, and VMA is determined.
Minnesota	Air voids Asphalt content Gradation Asphalt film thickness Mat density Confined edge density Unsupported edge density	Average deviation from a target value	The mixture is considered unacceptable and subject to reduced payment for mixture properties, including air voids, binder content, gradation, and asphalt film thickness, where the moving average of four tests exceeds the JMF limits. Lowest Pay Factor applies when there are multiple reductions on a single test. Separate pay factors are determined and applied for densities.

States	Acceptance Quality Characteristics (AQC's)	Quality Measure	Pay Factors
Mississippi	Air voids Asphalt content Gradation Voids in mineral aggregate Mat density	Average deviation from a target value	A fixed adjustment pay factors for the air voids, asphalt content, gradation, and VMA are provided. The minimum adjustment factor is applied to the contract unit price. A separate pay factor is applied for the mat density.
Missouri	Air voids Asphalt content Voids in mineral aggregate Mat density	PWL	A composite pay factor with 0.25, 0.25, 0.25, and 0.25 weight for asphalt content, air voids, VMA, and density is determined. The PFT for each lot when the density pay factor is not directly included, e.g., shoulder, is determined by considering 0.3333 weight for air voids, asphalt content, and VMA.
Montana	Volumetrics Density	Average deviation from a target value	Reduction pay factors for volumetrics and density are specified. Maximum allowable pay factor is 1.02. A \$3.00/ton price reduction in the unit bid price for plant mix surfacing will be applied for any start up mix represented by a test not meeting the volumetrics specified.
Nebraska	Air voids Mat density	Average deviation from a target value	A pay factors for the single test air voids and moving average of four air voids pay factors are determined (provided in a table). A separate pay factor for the density provided in a table is applied separately.
Nevada	Gradation Asphalt content Mat density	PWL	A composite pay factor with 0.25, 0.33, and 0.42 weight for gradation, asphalt content, and density is determined.
New Hampshire	Asphalt content Gradation Cross slope Mat density Ride quality Thickness	PWL	Two Tier analysis are used. Tier 1 item is to be used on specified projects that are on new locations, interstate projects, full depth reconstruction projects in rural areas or on reclamation projects in rural areas. For Tier 1, a composite pay factor with 0.15, 0.15, 0.20, 0.08, 0.12, and 0.30 weight for gradation, asphalt content, density, thickness, cross slopes, and ride smoothness is determined. Tier 2 item is to be used on specified projects that are inlay type projects, full depth reconstruction projects with maintenance of traffic phasing, projects with

States	Acceptance Quality Characteristics (AQC's)	Quality Measure	Pay Factors
			intersecting streets, projects with pavement tapers, bridge projects with short approach paving, projects where there are many manhole/drainage structures or driveways (generally in urban and suburban areas). For Tier 2, a composite pay factor with 0.25, 0.25, and 0.50 weight for gradation, asphalt content, and density is determined.
New Jersey	Mat Density Thickness Ride Quality	Percent Defective (PD)	Percent Pay Adjustments (PPA) for mat density, thickness, and ride quality as function of PD are determined.
New Mexico	Air voids Asphalt content Voids in mineral aggregate Mat density	PWL	A composite pay factor with 0.35, 0.35, 0.20, and 0.10 weight for density, air void, VMA, and asphalt content is determined.
New York	Air voids Gradation Mat density	Average deviation from a target value and PWL	For the air void and gradation quality adjustment factor based on the average absolute values are determined and used to adjust the payment. Density quality adjustment factors using PWL is used.
North Carolina	Air voids Asphalt content Gradation Mat density	Average deviation from a target value	For different mixtures, different weights are used to determine the pay factor.
North Dakota	Asphalt content Gradation Mat density	Average deviation from a target value	Using the deviation from target values, separate adjustment factors for asphalt content, gradation, and density are determined and applied.

States	Acceptance Quality Characteristics (AQC's)	Quality Measure	Pay Factors
Ohio	Asphalt content Gradation Mat density	Average deviation from a target value	Separate pay factors for the asphalt content and gradation are determined. When any pay factors for a specific Lot are less than 1.0, the lowest pay factor is used to calculate the payment. A separate pay factor is determined for mat density,
Oklahoma	Air voids Asphalt content Voids in mineral aggregate Mat density	PWL	A composite pay factor with 0.40, 0.30, 0.20, and 0.10 weight for density, air void, asphalt content, and VMA is determined.
Oregon	Asphalt content Gradation Mat density	PWL	A composite pay factor with 0.28, 0.28, and 0.44 weight for asphalt content, gradation, and density is determined.
Pennsylvania	Asphalt content Percent passing the #200 sieve Percent passing the primary control sieve Mat density	PWL	A composite pay factor with 0.30, 0.10, 0.10, and 0.5 weight for asphalt content, percent passing the #200 sieve, percent passing the primary control sieve, and density is determined.
Rhode Island	Air voids Asphalt content Mat density Joint density	Average deviation from a target value	Separate pay adjustment factors for air voids, asphalt content, mat density, and joint density are used and applied to the contract price.
South Carolina	Air voids Asphalt content Voids in mineral aggregate Mat density	PWL	A composite pay factor with 0.30, 0.25, 0.10, and 0.35 weight for asphalt content, air void, VMA, and density is determined.

States	Acceptance Quality Characteristics (AQC's)	Quality Measure	Pay Factors
South Dakota	Air voids Mat density	PWL	A composite pay factor with 0.50 weight for both air voids and density is determined.
Tennessee	Asphalt content Gradation Mat density	Average deviation from a target value	Separate pay adjustment factors for asphalt content and gradation are applied to the contract price. For the density pay adjustment factor, the percent of total payment to be deducted is 5 times the percent the average in-place density for each lot that fails to meet.
Texas	Bulk specific gravity Mat Density	Average deviation from a target value	An adjustment factor for Gmb, called Production Payment Adjustment Factor, and an adjustment factor for mat density, called Placement Payment Adjustment Factor are determined. Total adjusted pay (TAP) is based on the applicable payment adjustment factors for production and placement for each lot (average for production and placement).
Utah	Asphalt content Gradation Mat density Joint density	PWL	The Department applies one Incentive/Disincentive for the lowest dollar value for Gradation/Asphalt Content, one Incentive/Disincentive for Mat Density, and one Incentive/Disincentive for Longitudinal Joint Density.
Vermont	Air voids Mat density	PWL	Separate pay adjustment factors for air void and density are applied to the contract price.
Virginia	Asphalt content Gradation Mat density	Average deviation from a target value	If a lot of material does not conform to the acceptance requirements for asphalt content and gradation, the adjustment points are applied. If the total adjustment for a lot is greater than 25 points, the Contractor shall remove the failing material from the road. If the total adjustment is 25 points or less and the Contractor does not elect to remove and replace the material, the unit price for the material will be reduced 1 percent of the unit price bid for each adjustment point the material is outside of the process tolerance. Payment schedule for lot densities is applied separately.
Washington	Air voids Asphalt content Gradation	PWL	A composite pay factor for air voids, asphalt content, gradation, VMA is determined. Compaction price adjustment is determined and applied separately.

States	Acceptance Quality Characteristics (AQC's)	Quality Measure	Pay Factors
	Voids in mineral aggregate Mat density		
West Virginia	Asphalt content Percent passing the 75 µm Mat density	PWL	A composite pay factor with 0.25, 0.25, and 0.50 weight for asphalt content, percent passing the 75 µm, and density is determined.
Wisconsin	Air voids Asphalt content Gradation Voids in mineral aggregate Mat density	Average deviation from a target value	Payment adjustment in percent of the contract unit price for air voids, asphalt content, gradation, and VMA are specified. Reduction in pay based on the nonconforming property with lowest percent pay is applied. Density Incentive/disincentive are applied separately.
Wyoming	Asphalt content Gradation Mat density	PWL	Separate pay adjustment factors for asphalt content, gradation, and mat density are applied to the contract price.

**APPENDIX B: PROJECT LEVEL CORRELATIONS CPF VS
CRACKING FOR DENSE GRADED MIXTURES**

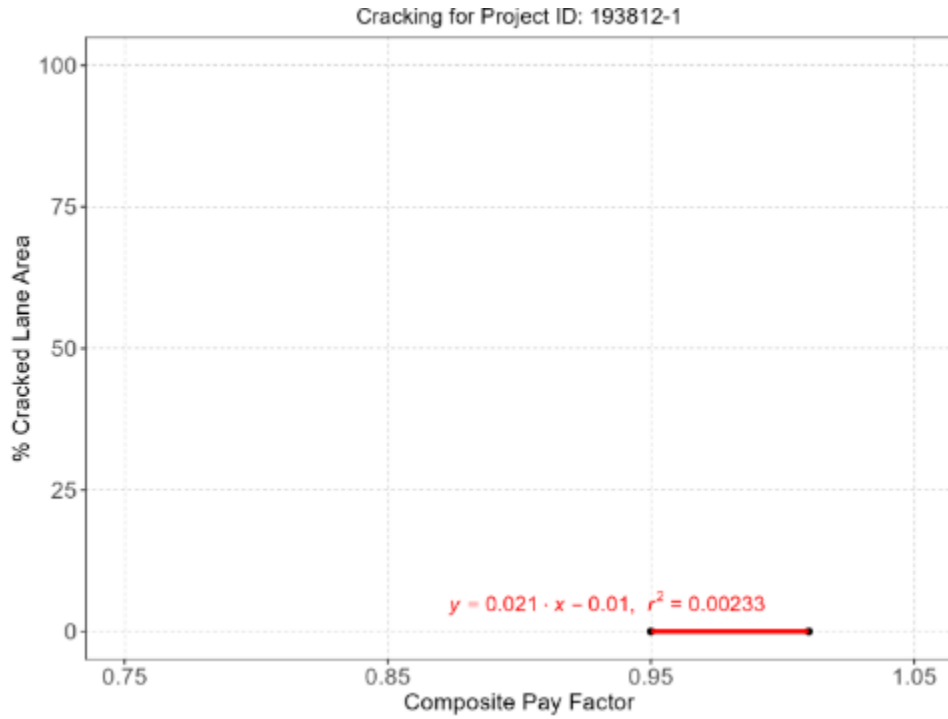


Figure B.1. Total Cracking vs Composite Pay Factor for Project 193812-1

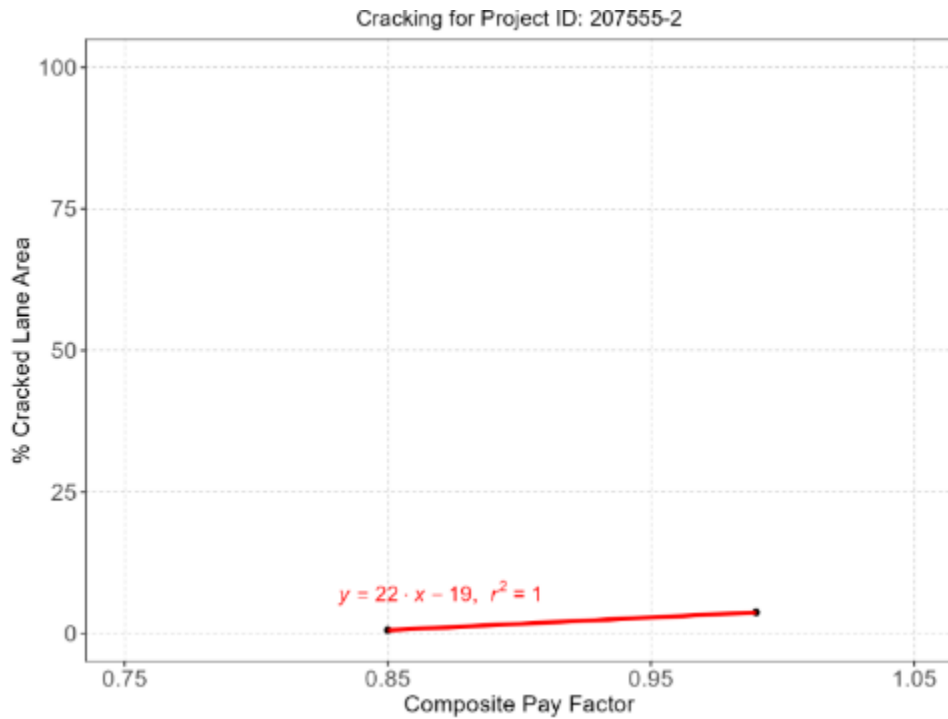


Figure B.2. Total Cracking vs Composite Pay Factor for Project 207555-2

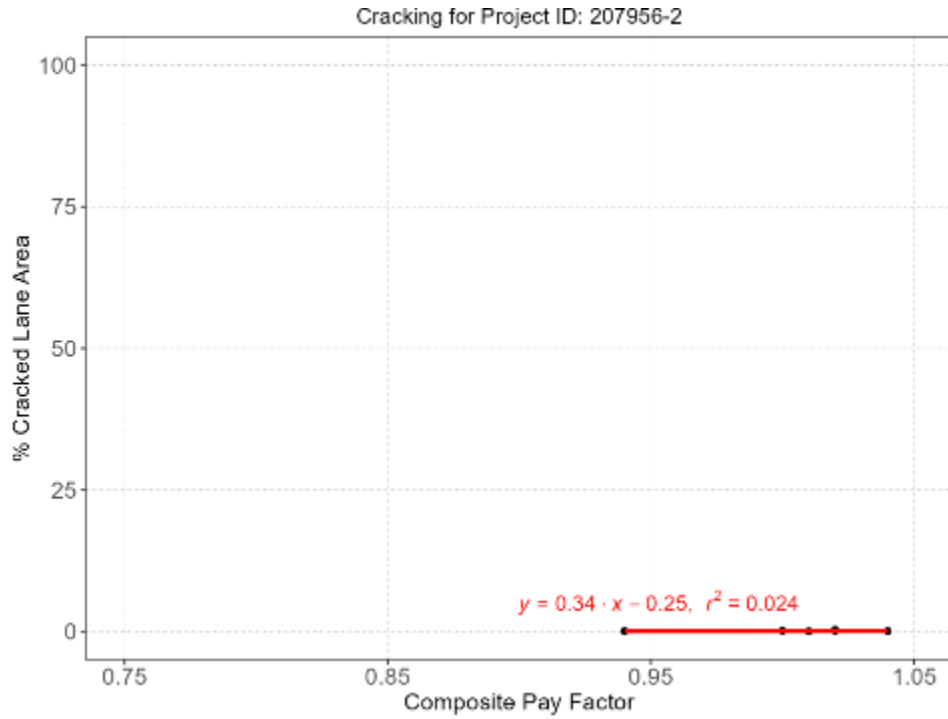


Figure B.3. Total Cracking vs Composite Pay Factor for Project 207956-2

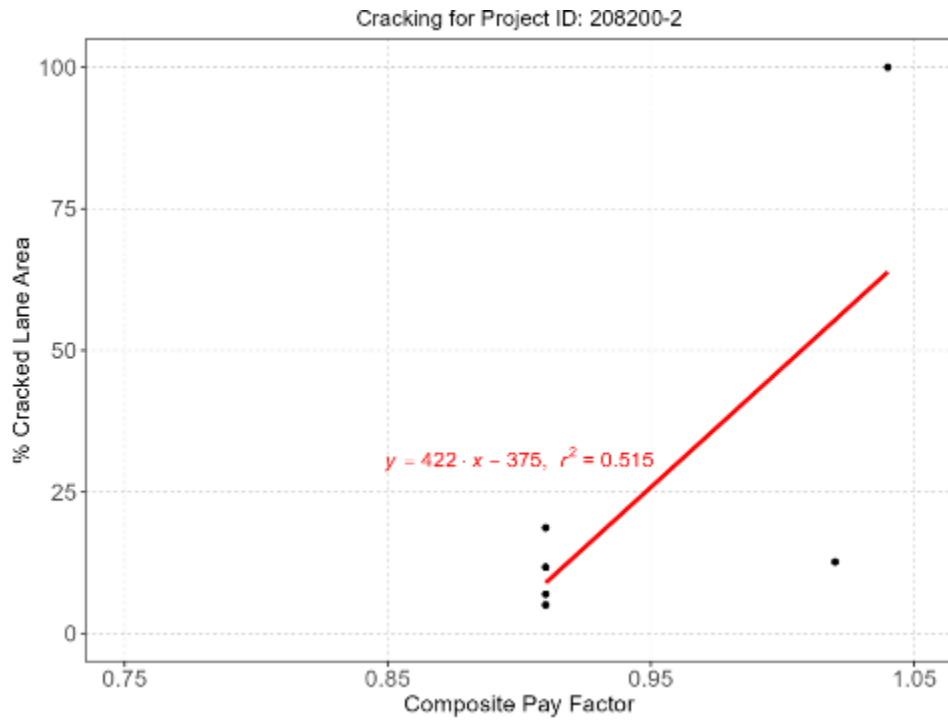


Figure B.4. Total Cracking vs Composite Pay Factor for Project 208200-2

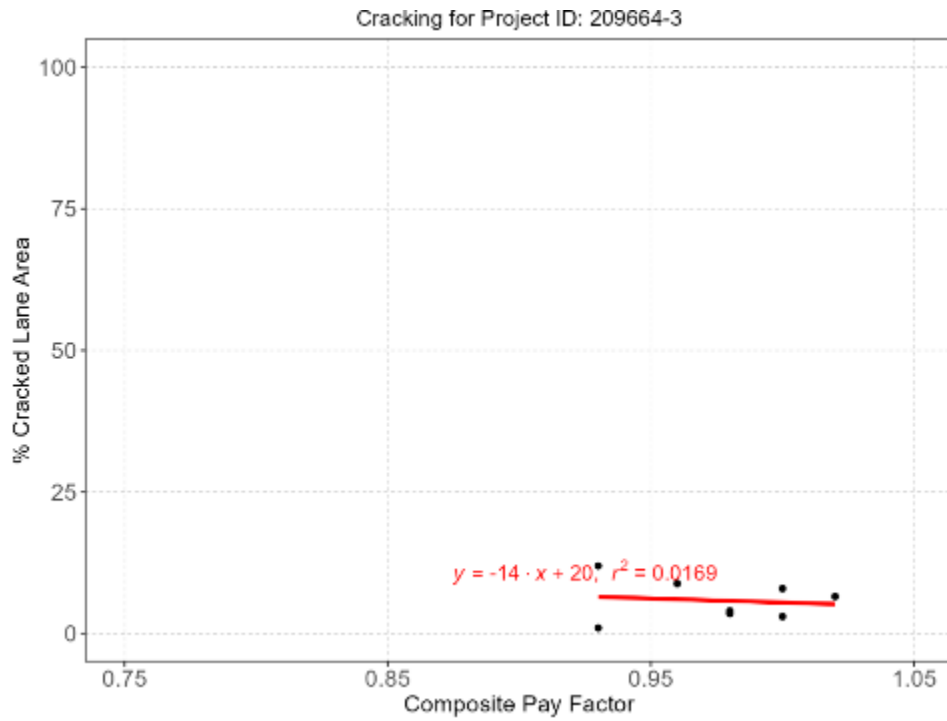


Figure B.5. Total Cracking vs Composite Pay Factor for Project 209664-3

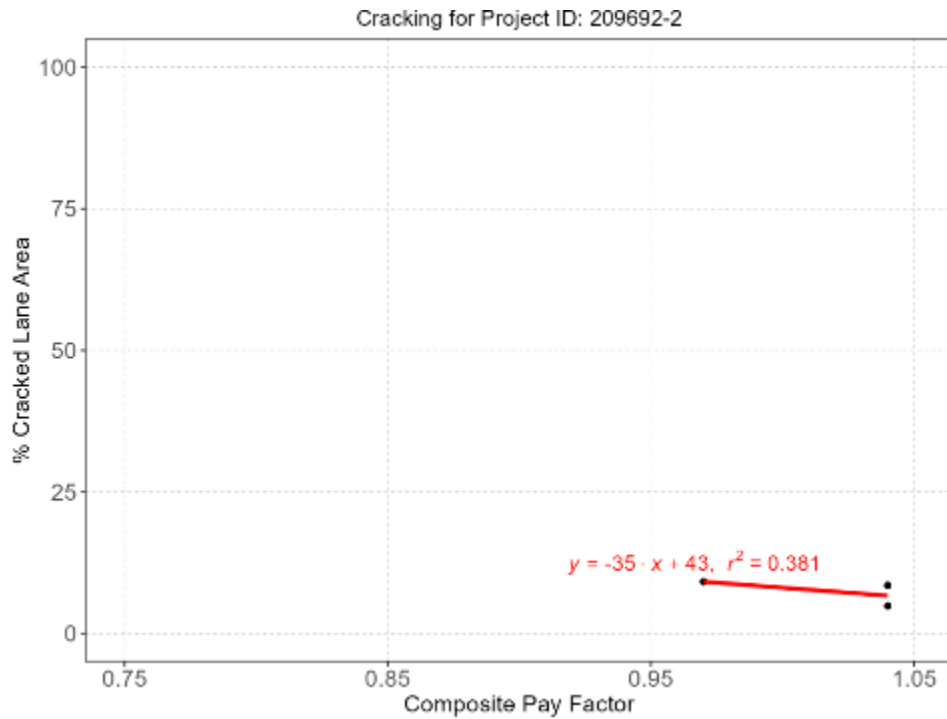


Figure B.6. Total Cracking vs Composite Pay Factor for Project 209692-2

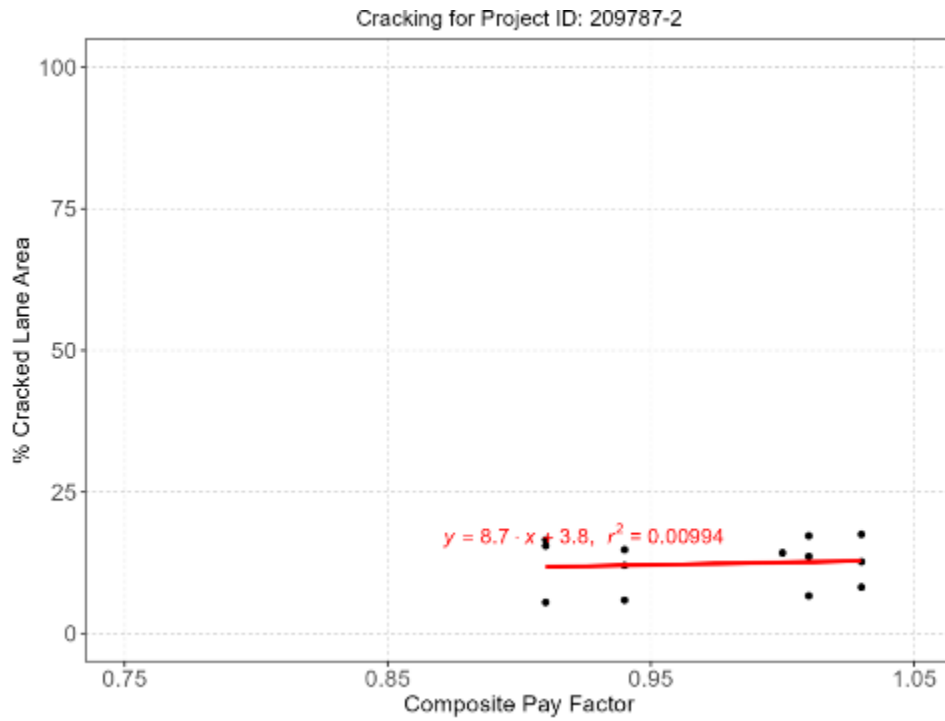


Figure B.7. Total Cracking vs Composite Pay Factor for Project 209787-2

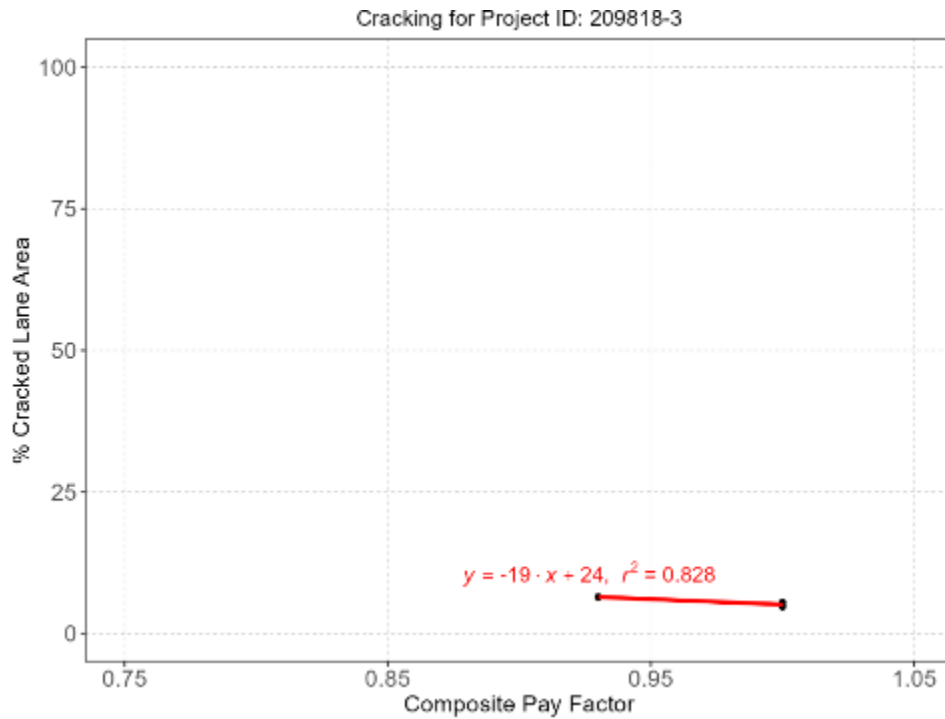


Figure B.8. Total Cracking vs Composite Pay Factor for Project 209818-3

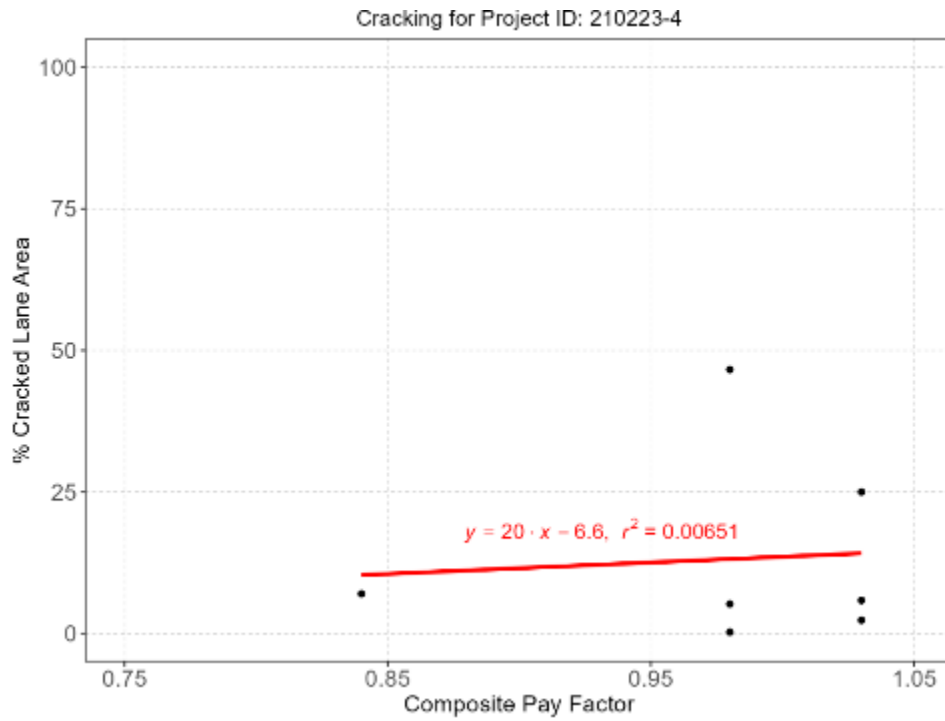


Figure B.9. Total Cracking vs Composite Pay Factor for Project 210223-4

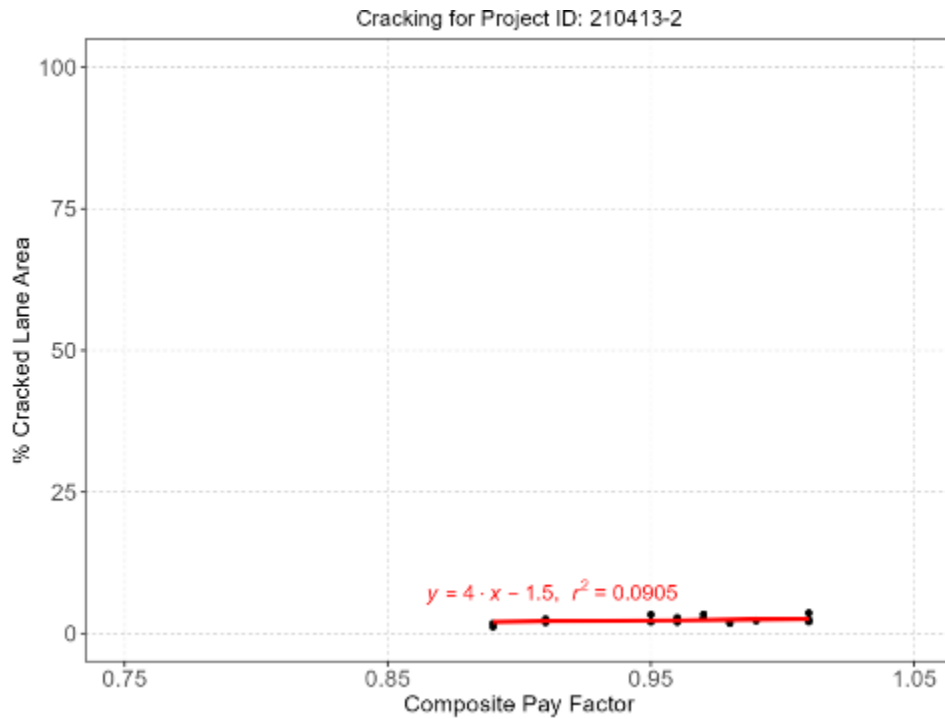


Figure B.10. Total Cracking vs Composite Pay Factor for Project 210413-2

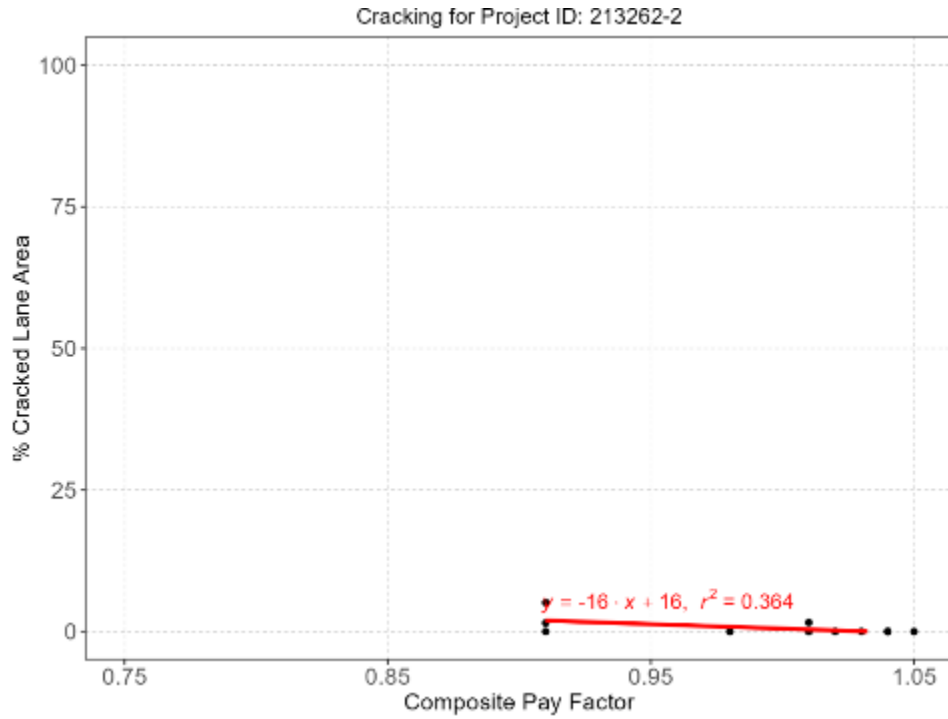


Figure B.11. Total Cracking vs Composite Pay Factor for Project 213262-2

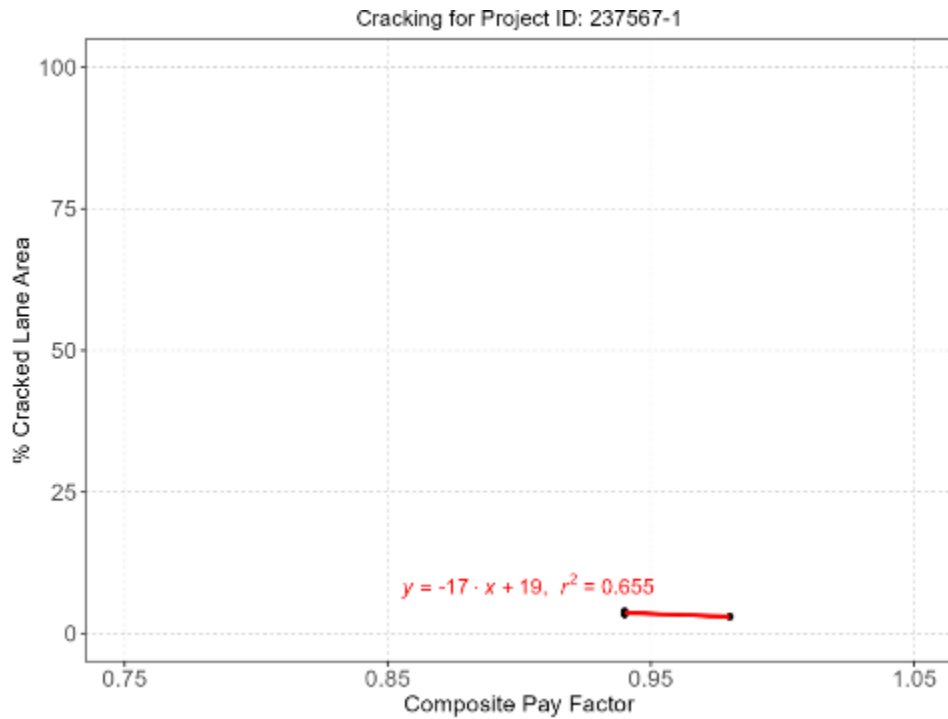


Figure B.12. Total Cracking vs Composite Pay Factor for Project 237567-1

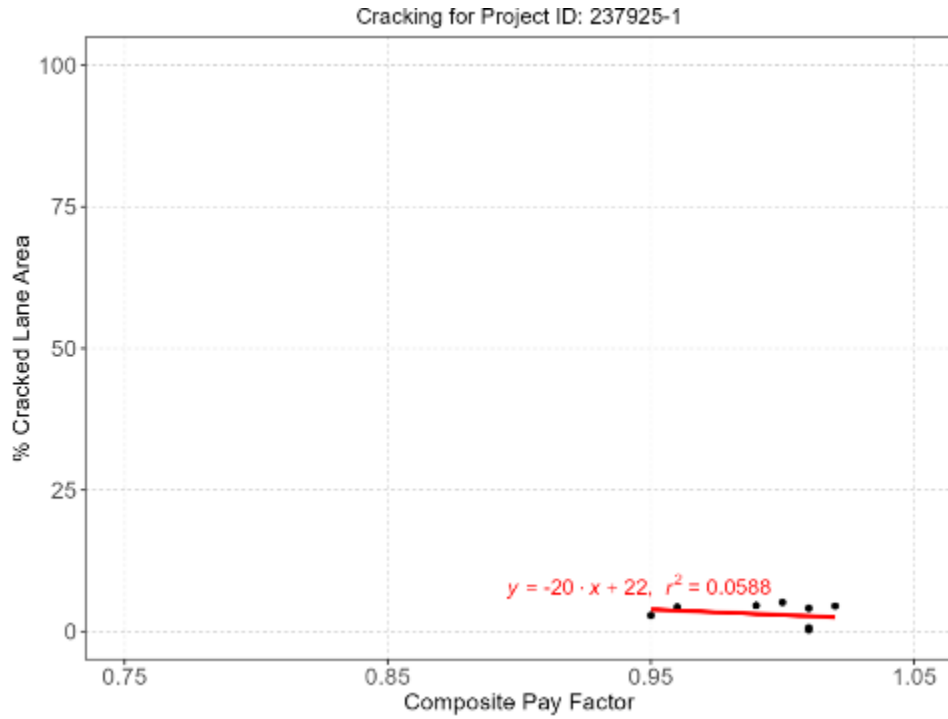


Figure B.13. Total Cracking vs Composite Pay Factor for Project 237925-1

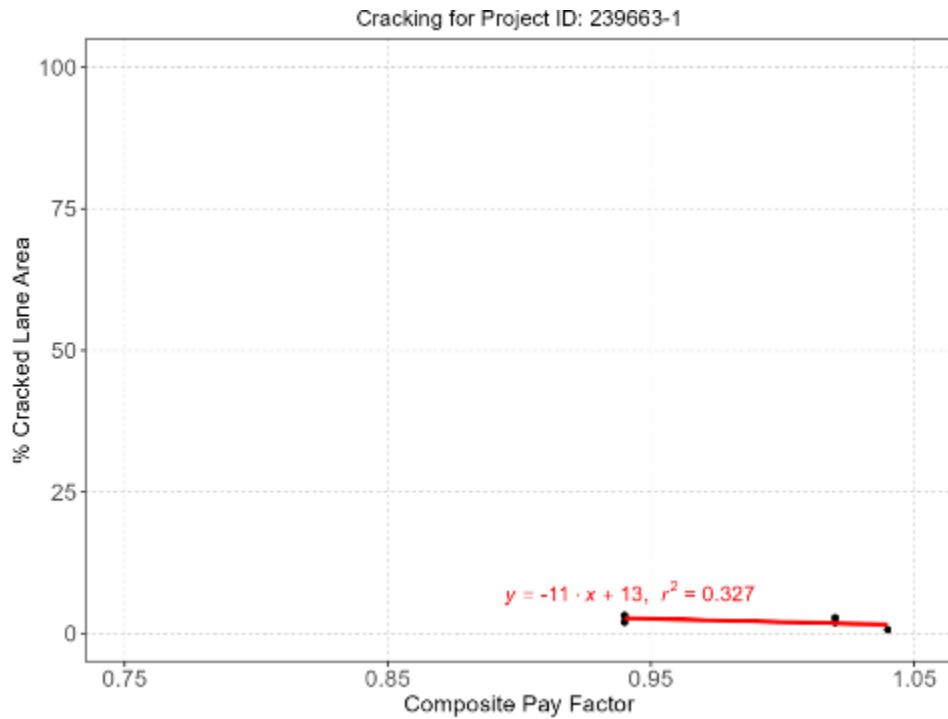


Figure B.14. Total Cracking vs Composite Pay Factor for Project 239663-1

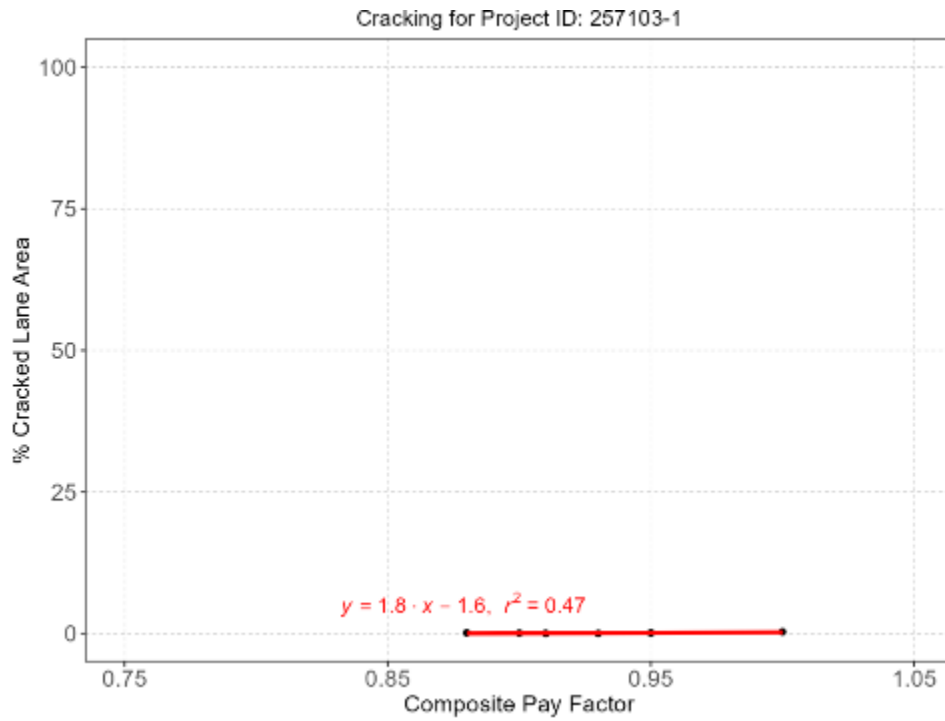


Figure B.15. Total Cracking vs Composite Pay Factor for Project 257103-1

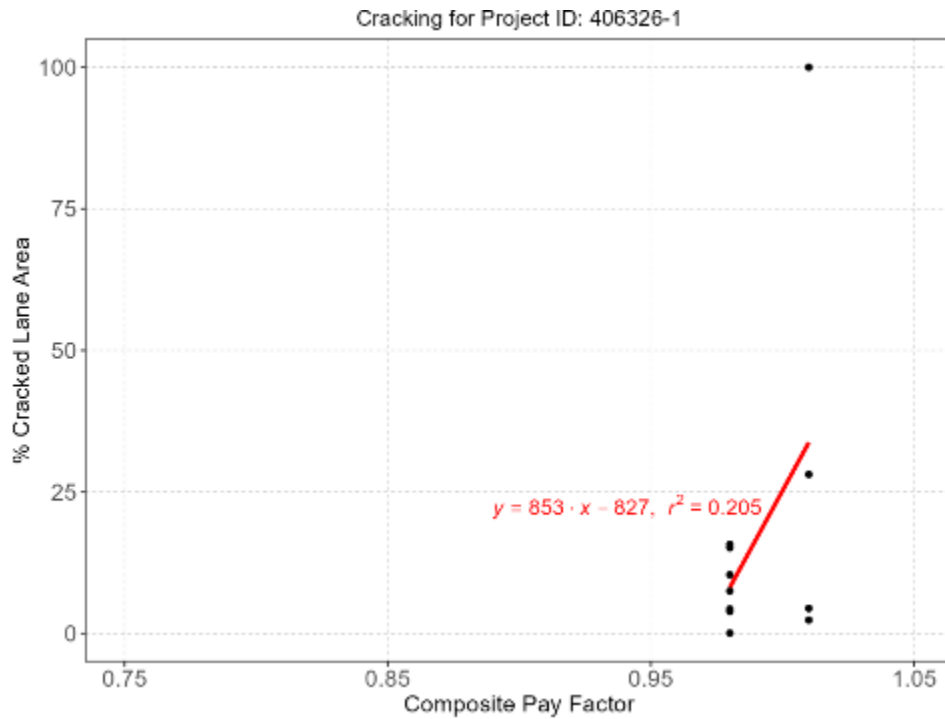


Figure B.16. Total Cracking vs Composite Pay Factor for Project 406326-1

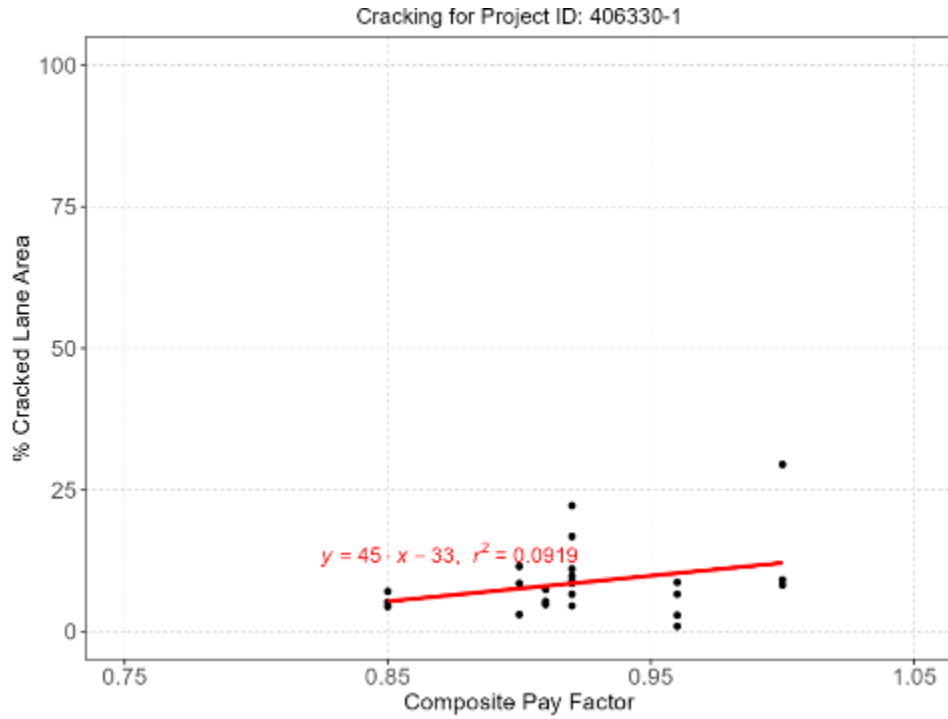


Figure B.17. Total Cracking vs Composite Pay Factor for Project 406330-1

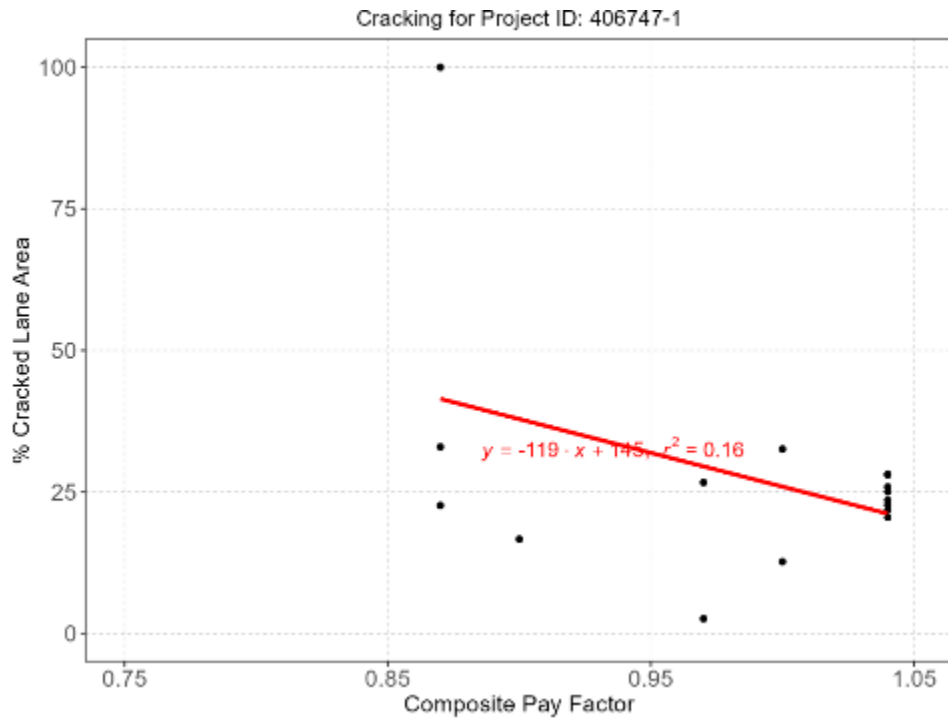


Figure B.18. Total Cracking vs Composite Pay Factor for Project 406747-1

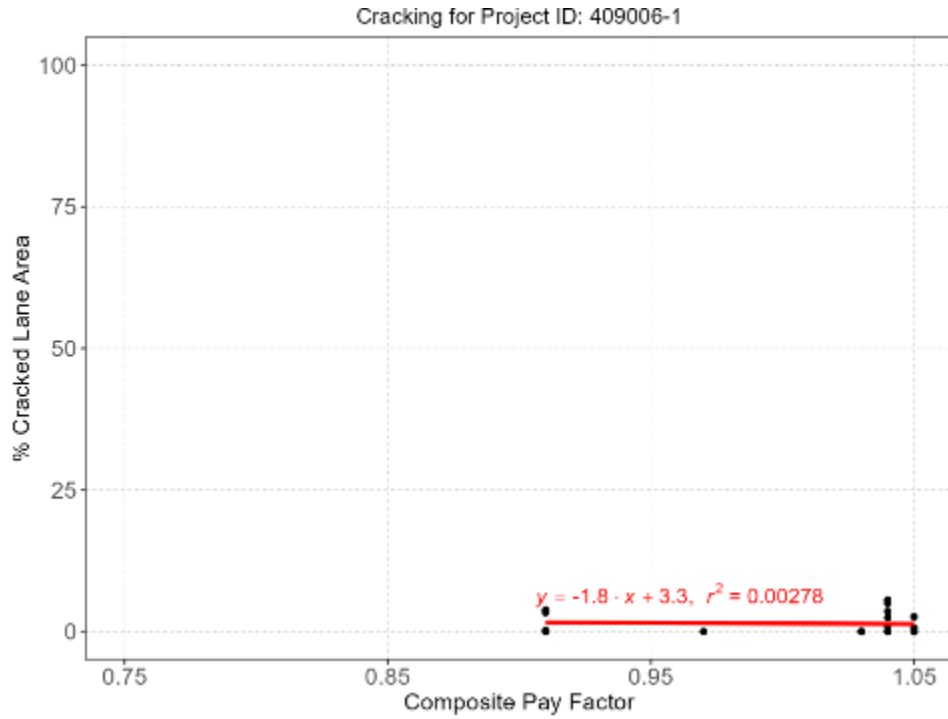


Figure B.19. Total Cracking vs Composite Pay Factor for Project 409006-1

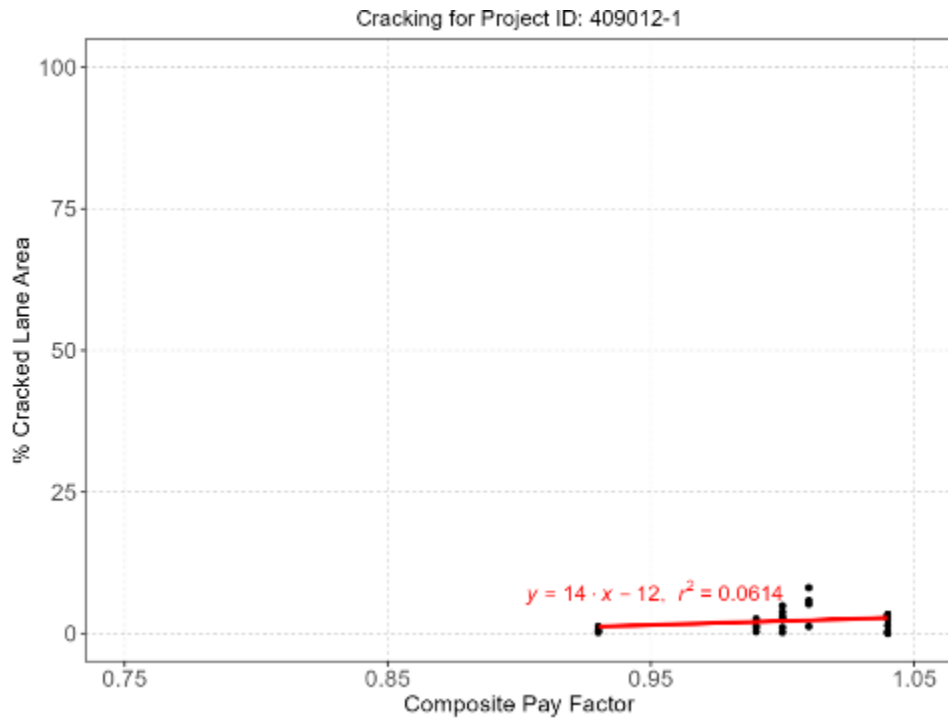


Figure B.20. Total Cracking vs Composite Pay Factor for Project 409012-1

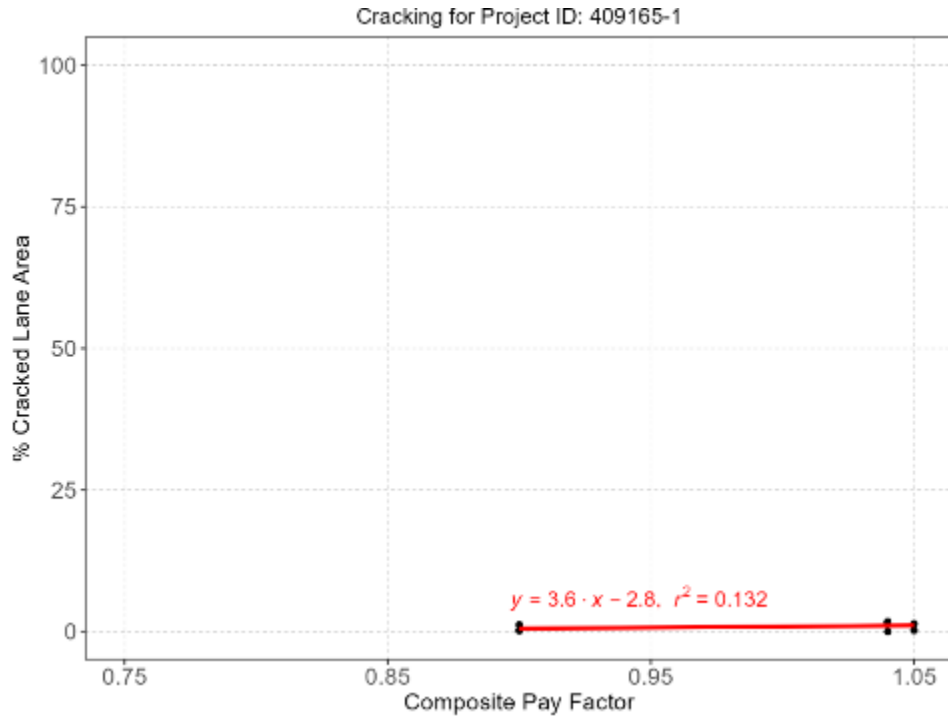


Figure B.21. Total Cracking vs Composite Pay Factor for Project 409165-1

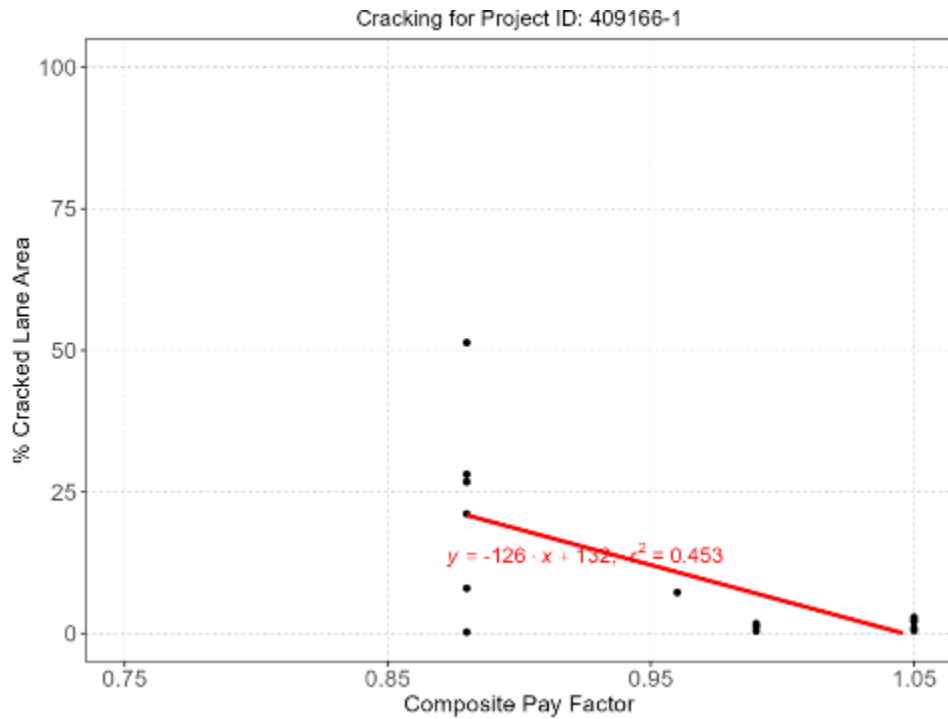


Figure B.22. Total Cracking vs Composite Pay Factor for Project 409166-1

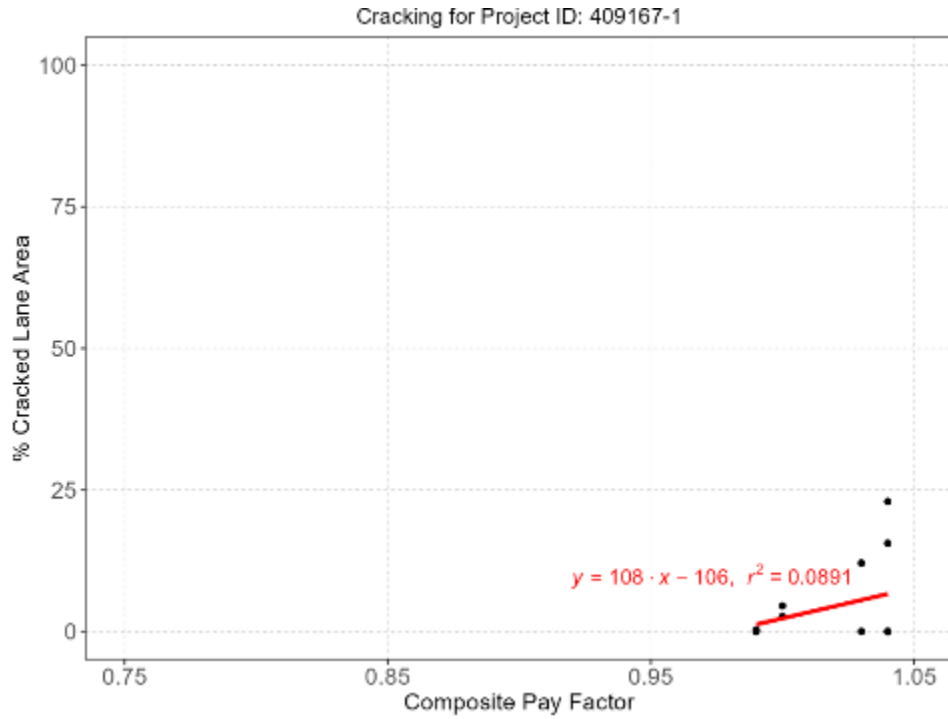


Figure B.23. Total Cracking vs Composite Pay Factor for Project 409167-1

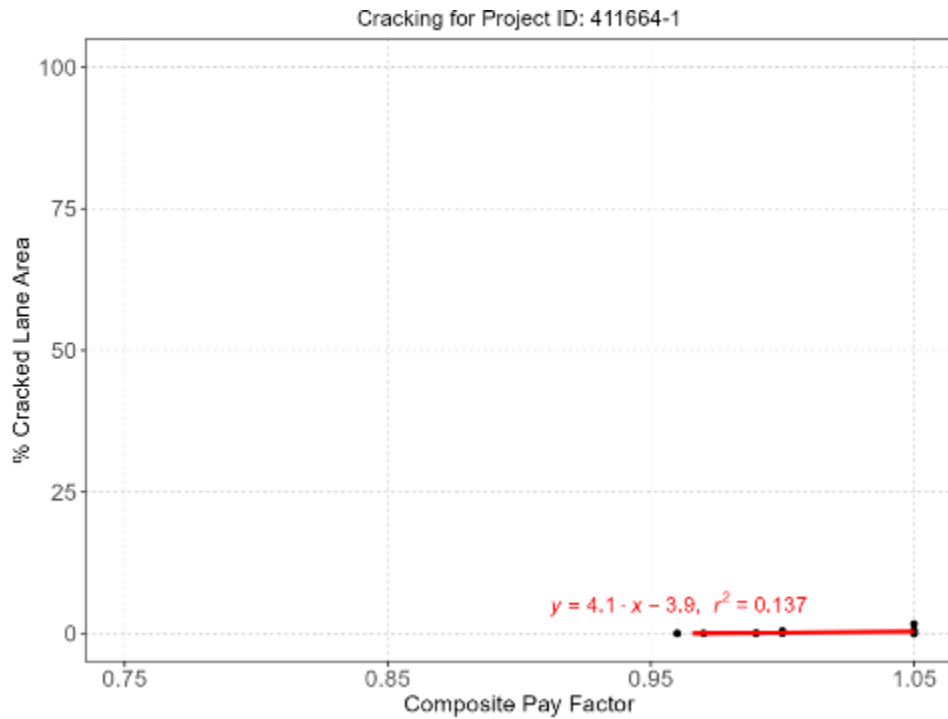


Figure B.24. Total Cracking vs Composite Pay Factor for Project 411664-1

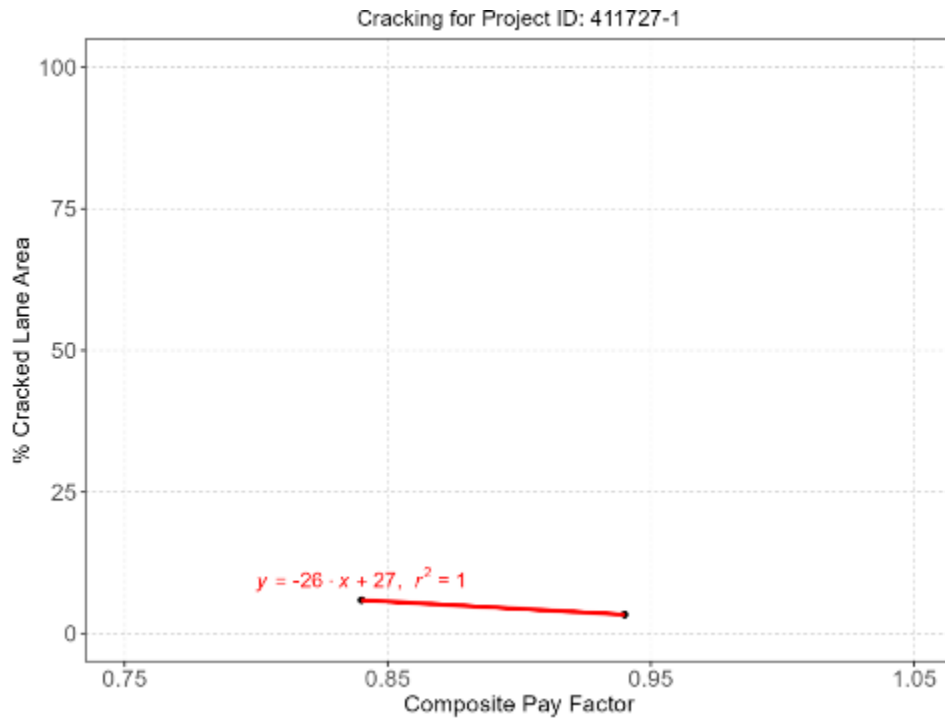


Figure B.25. Total Cracking vs Composite Pay Factor for Project 411727-1

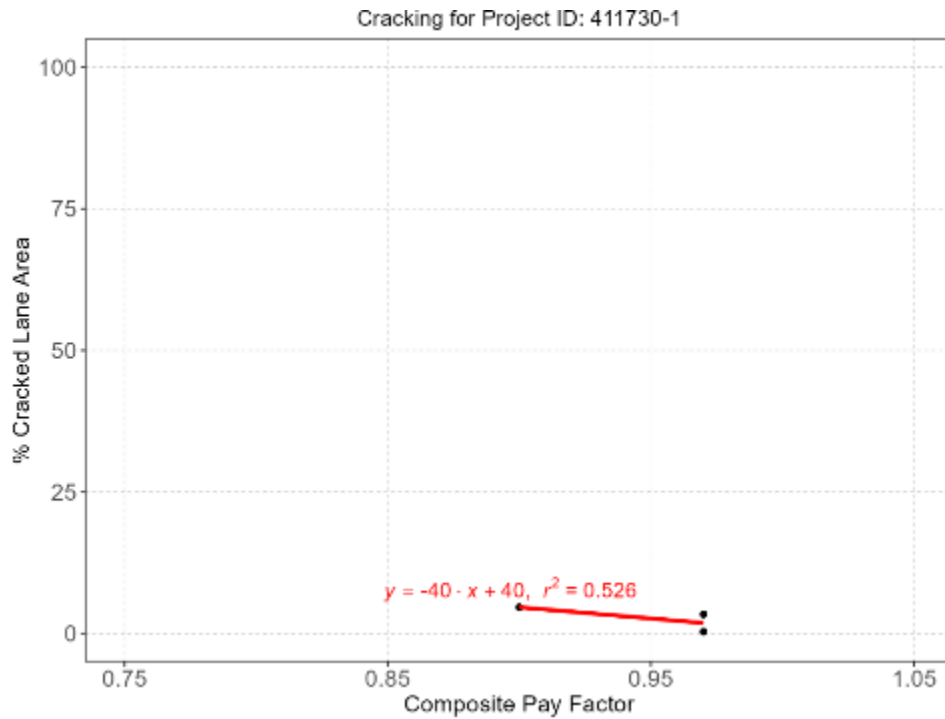


Figure B.26. Total Cracking vs Composite Pay Factor for Project 411730-1

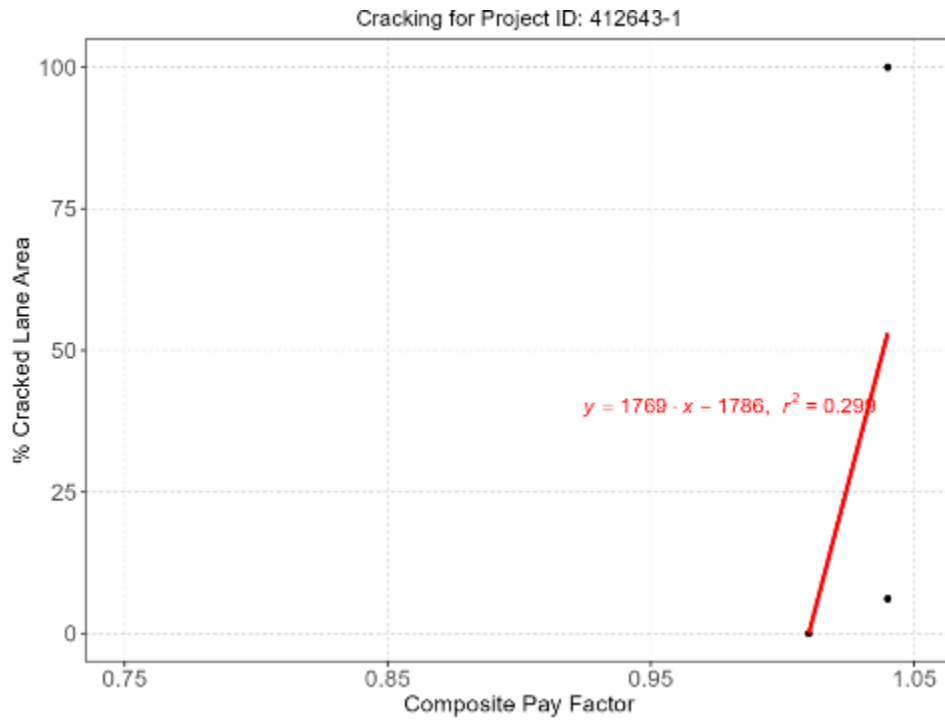


Figure B.27. Total Cracking vs Composite Pay Factor for Project 412643-1

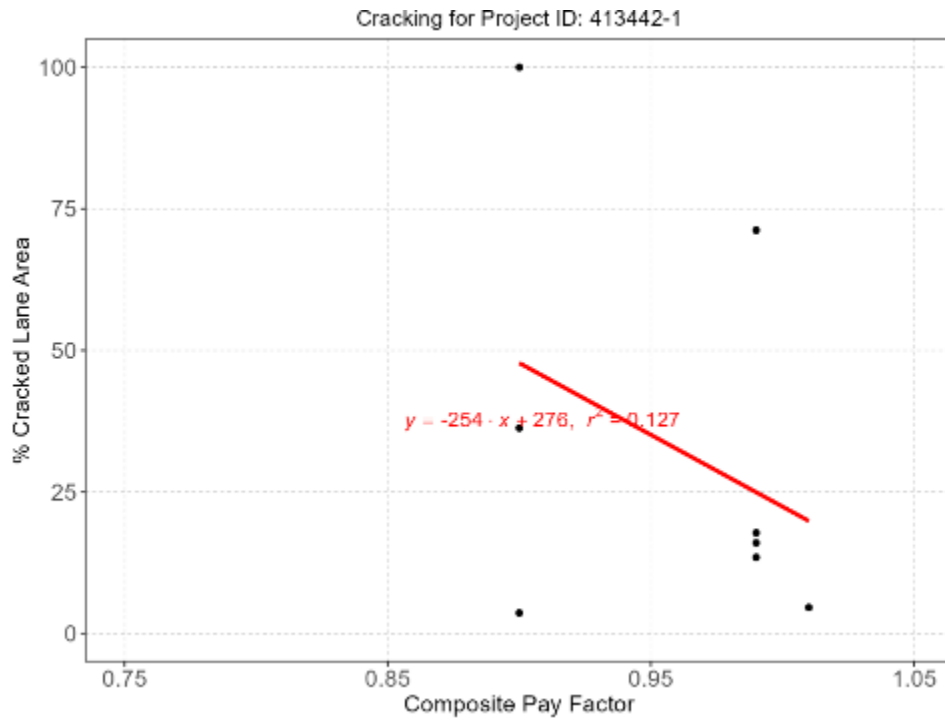


Figure B.28. Total Cracking vs Composite Pay Factor for Project 413442-1

**APPENDIX C: PROJECT LEVEL CORRELATIONS CPF VS
RUTTING FOR DENSE GRADED MIXTURES**

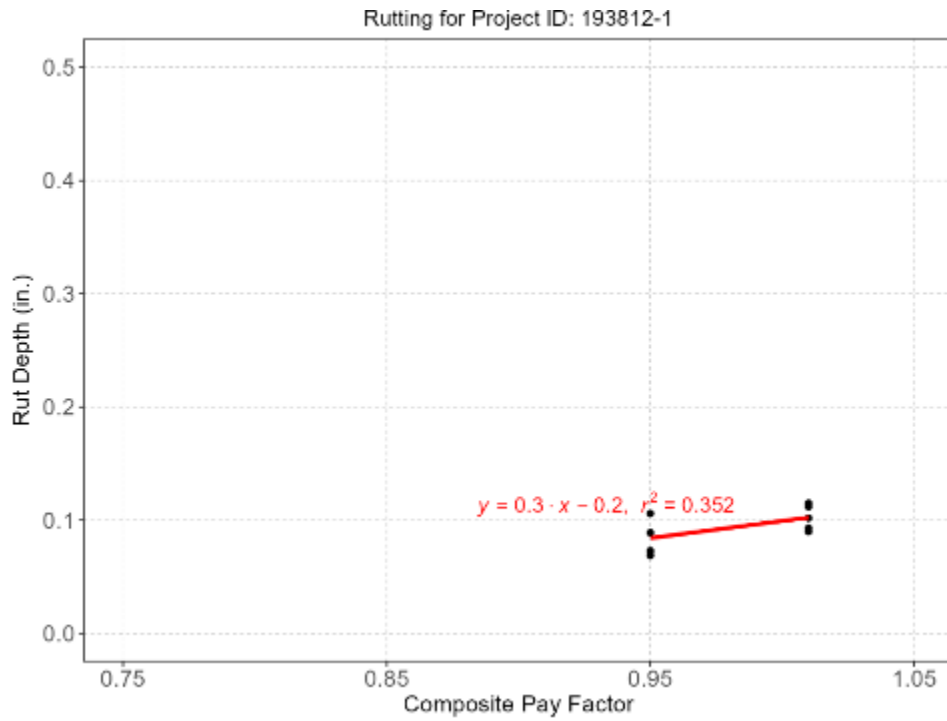


Figure C.1. Rutting vs Composite Pay Factor for Project 193812-1

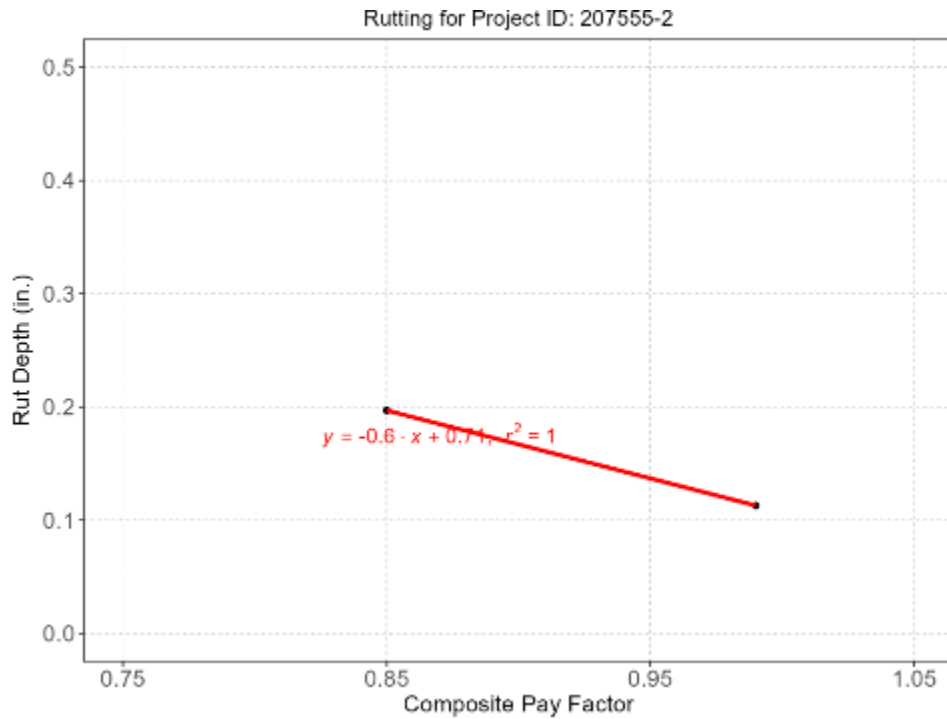


Figure C.2. Rutting vs Composite Pay Factor for Project 207555-2

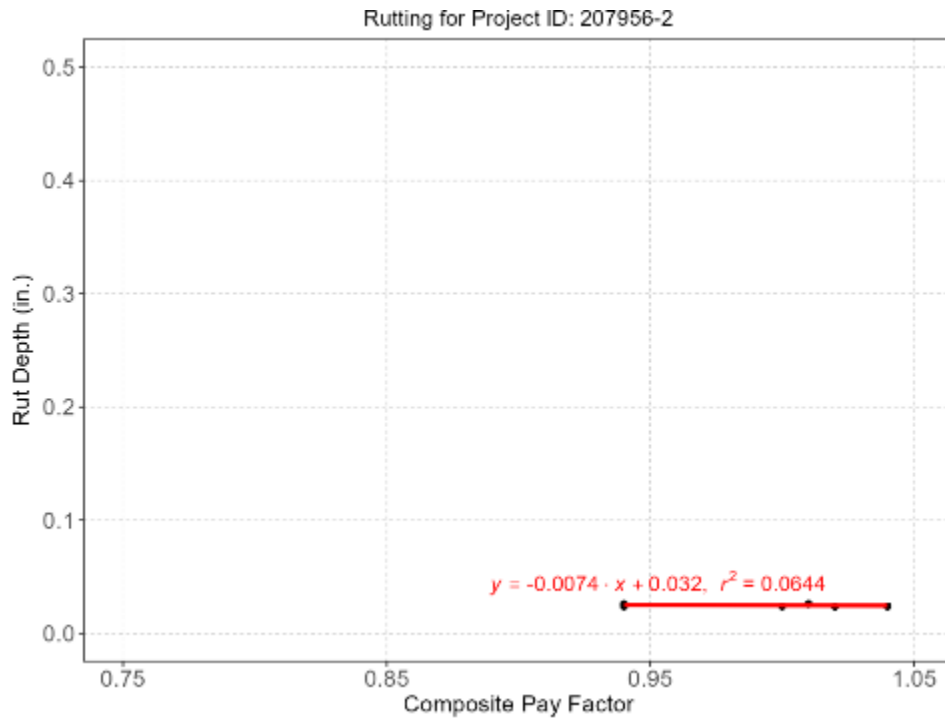


Figure C.3. Rutting vs Composite Pay Factor for Project 207956-2

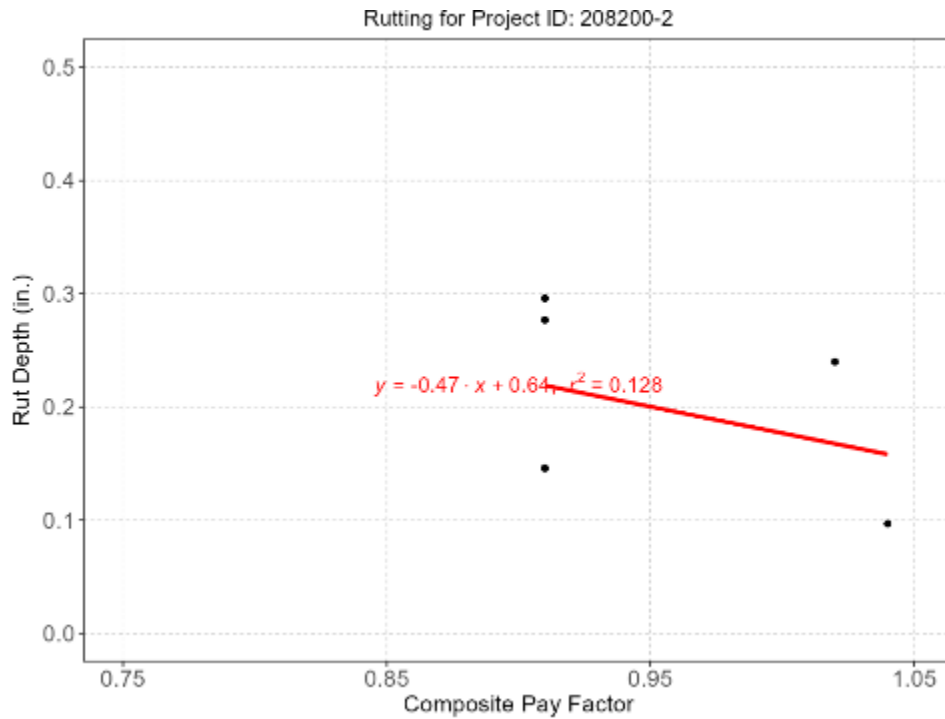


Figure C.4. Rutting vs Composite Pay Factor for Project 208200-2

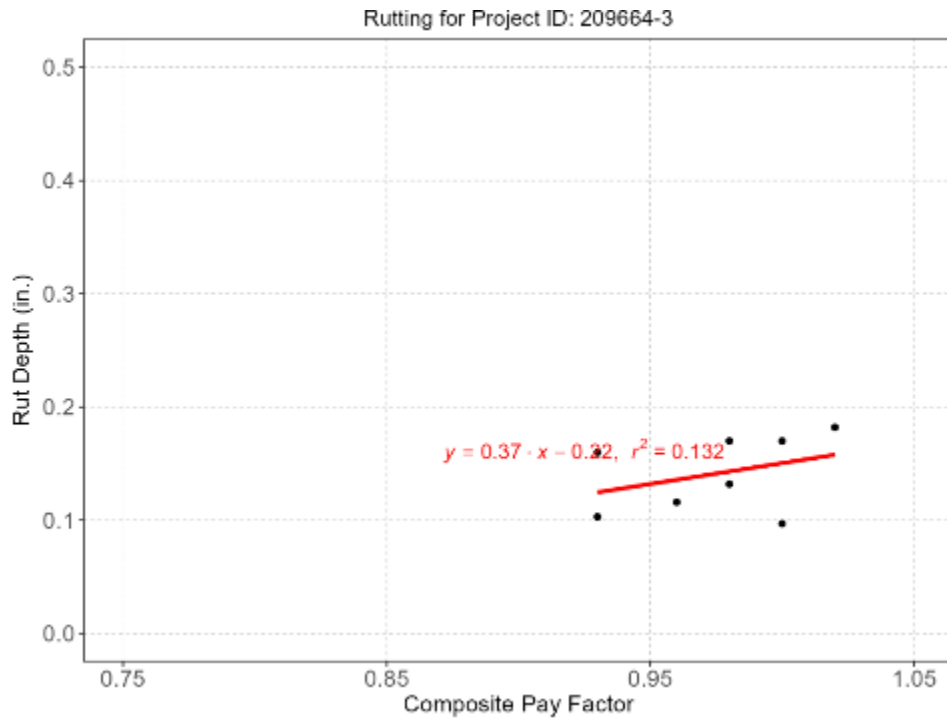


Figure C.5. Rutting vs Composite Pay Factor for Project 209664-3

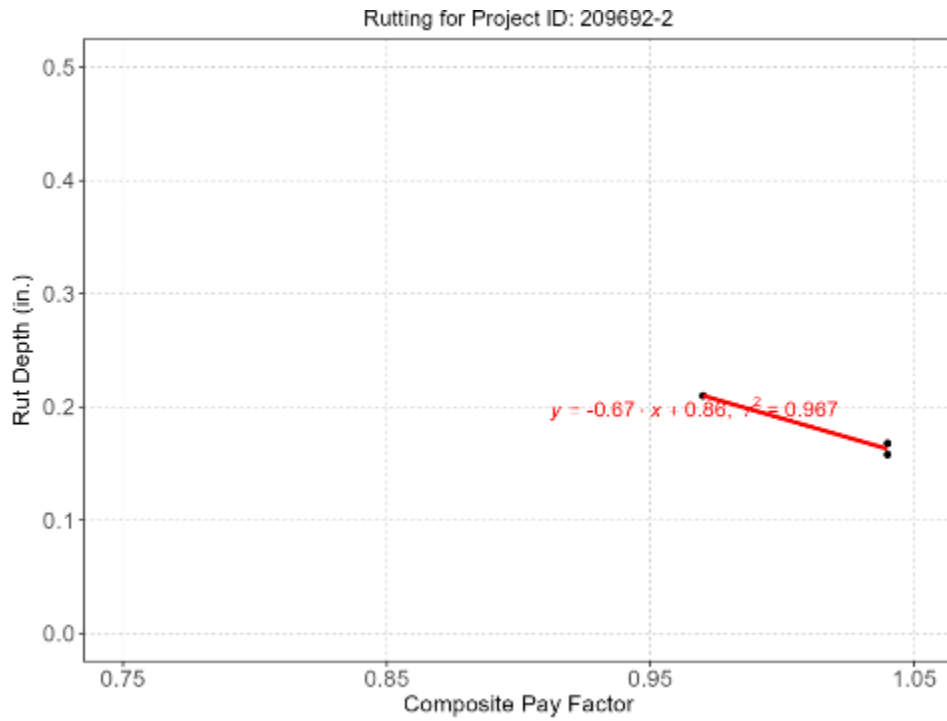


Figure C.6. Rutting vs Composite Pay Factor for Project 209692-2

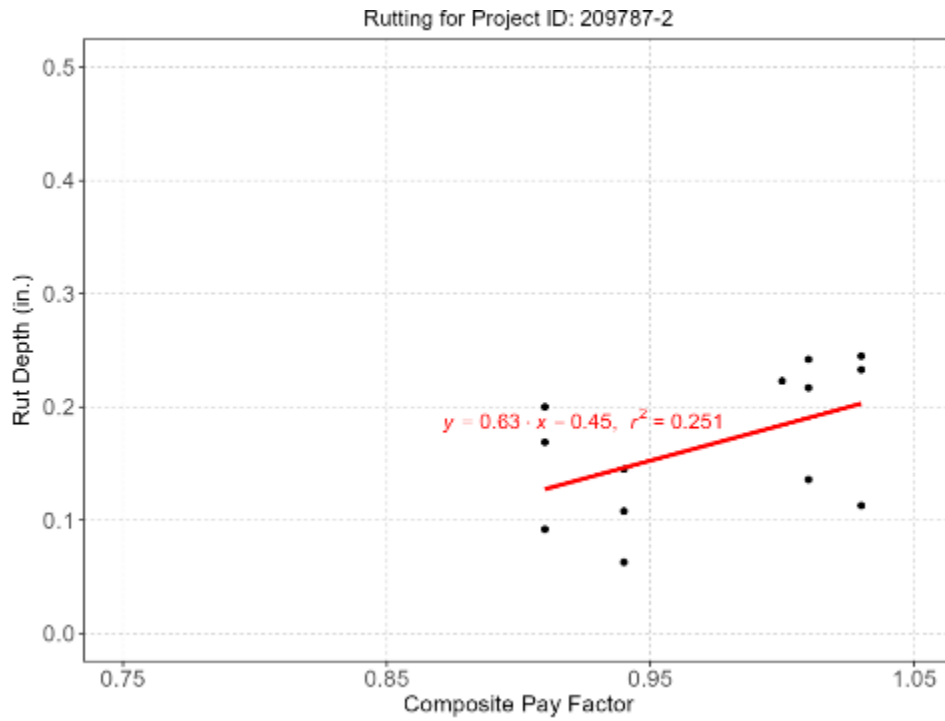


Figure C.7. Rutting vs Composite Pay Factor for Project 209787-2

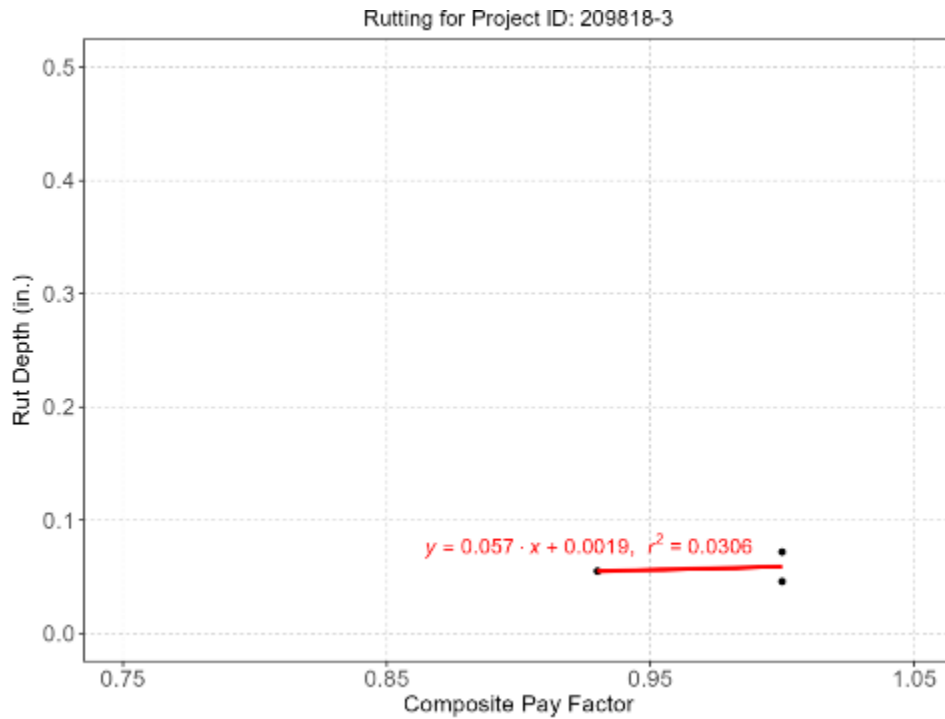


Figure C.8. Rutting vs Composite Pay Factor for Project 209818-3

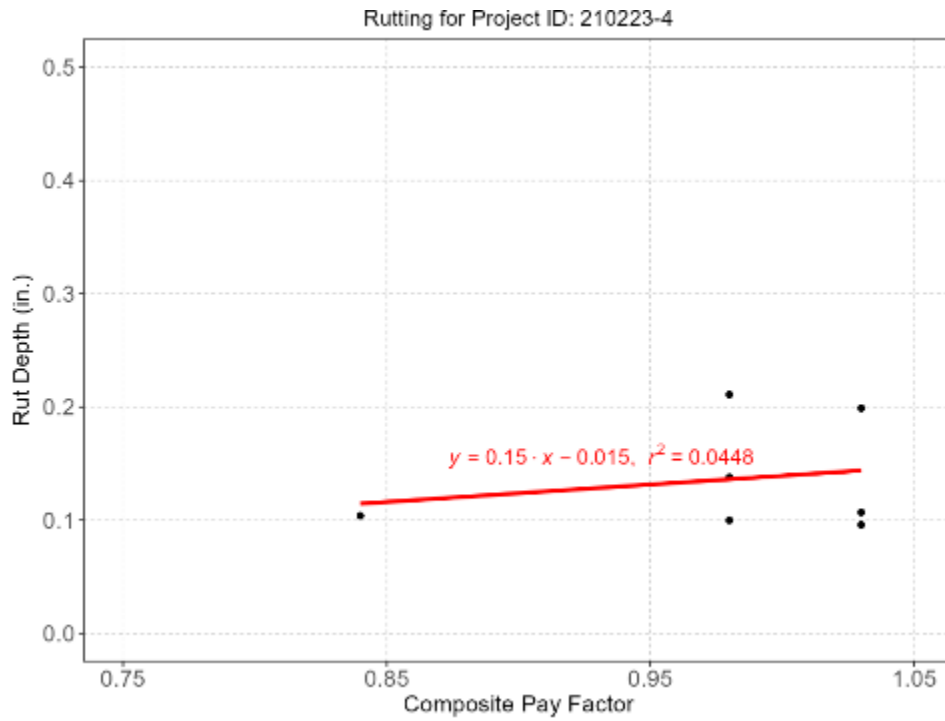


Figure C.9. Rutting vs Composite Pay Factor for Project 210223-4

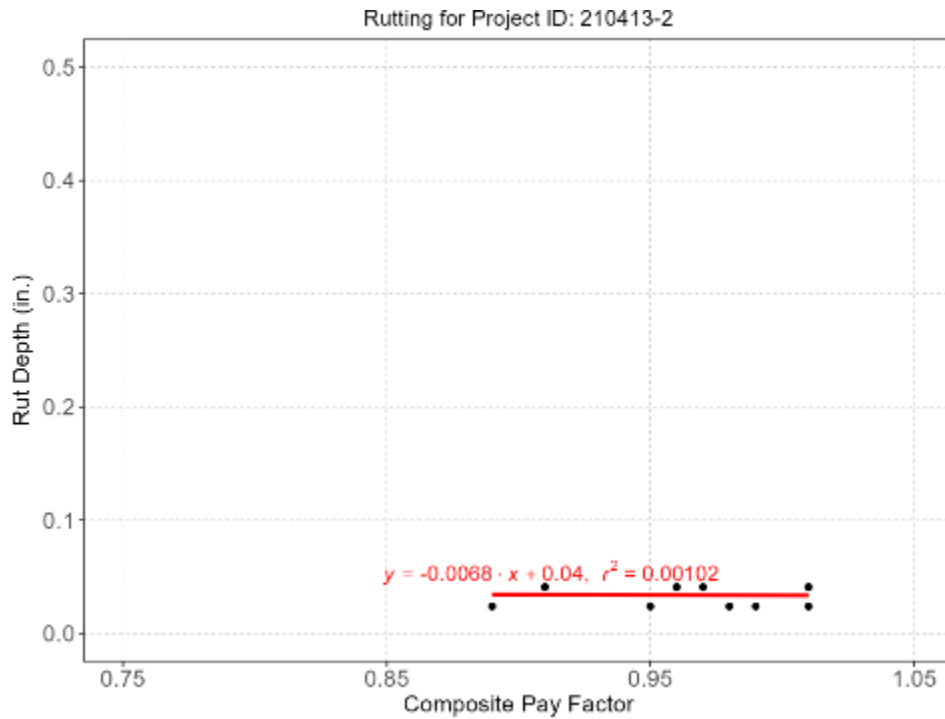


Figure C.10. Rutting vs Composite Pay Factor for Project 210413-2

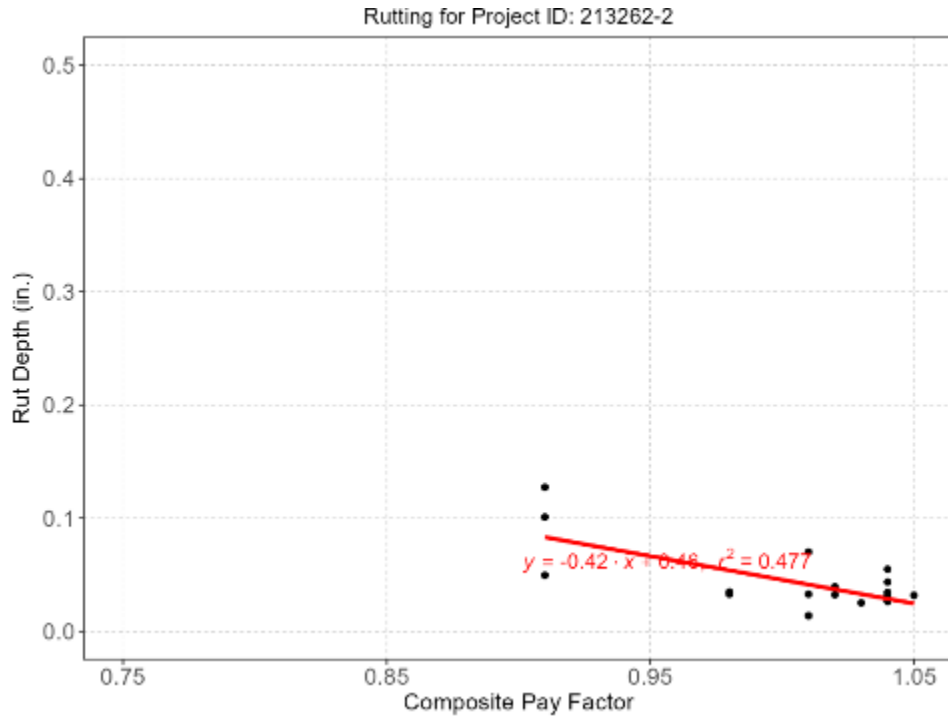


Figure C.11. Rutting vs Composite Pay Factor for Project 213262-2

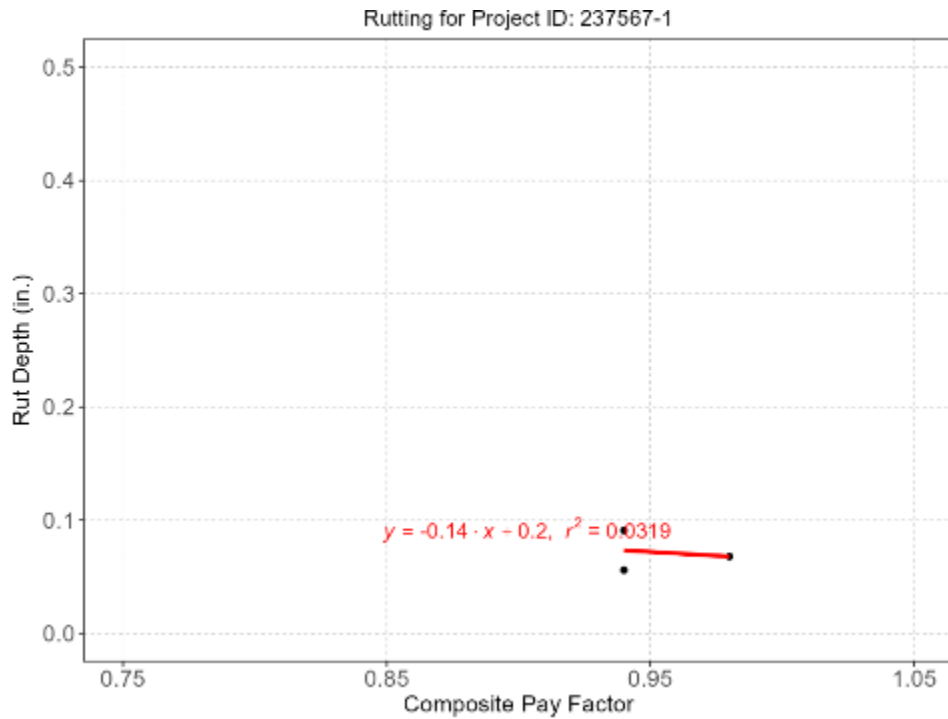


Figure C.12. Rutting vs Composite Pay Factor for Project 237567-1

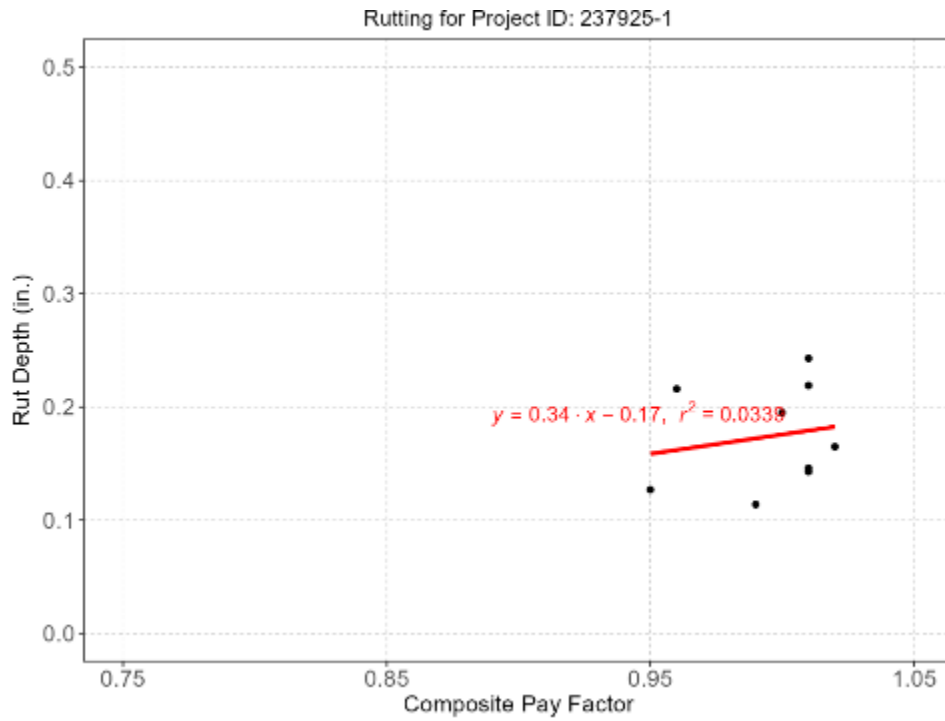


Figure C.13. Rutting vs Composite Pay Factor for Project 237925-1

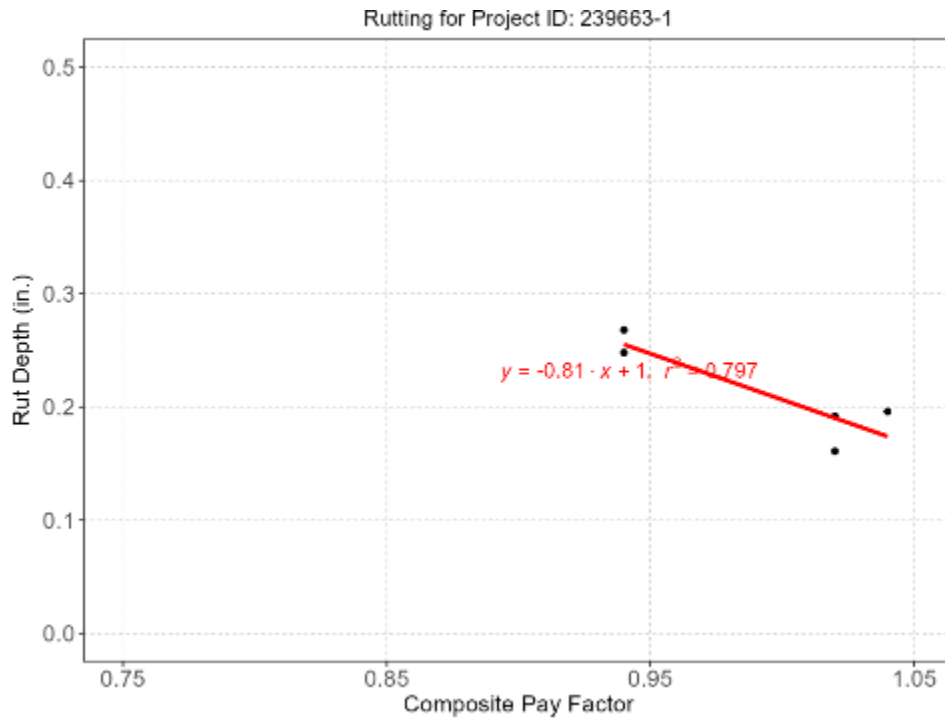


Figure C.14. Rutting vs Composite Pay Factor for Project 239663-1

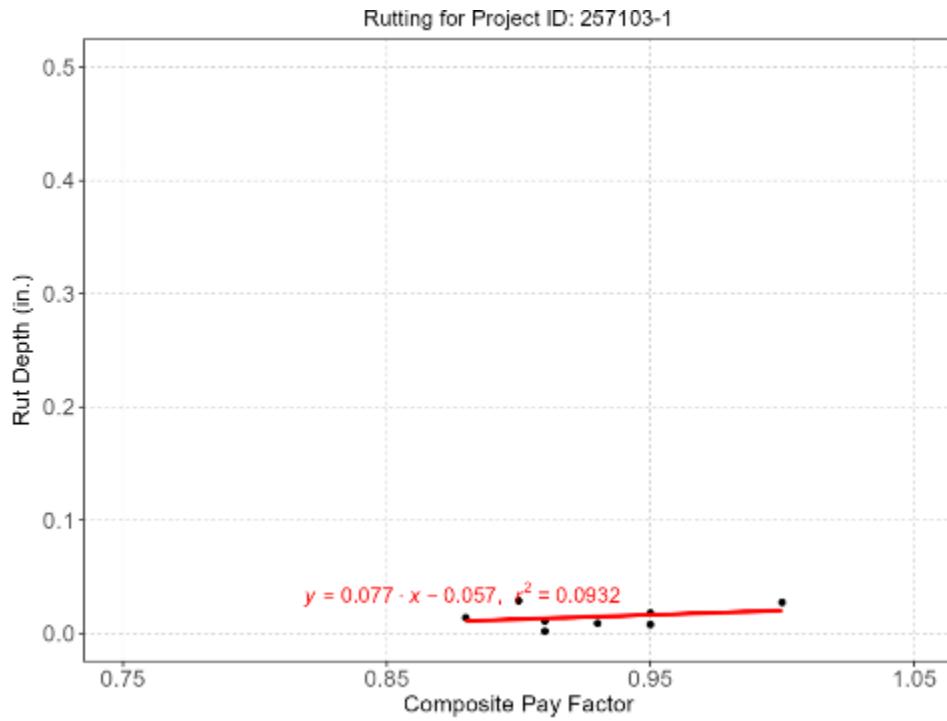


Figure C.15. Rutting vs Composite Pay Factor for Project 257103-1

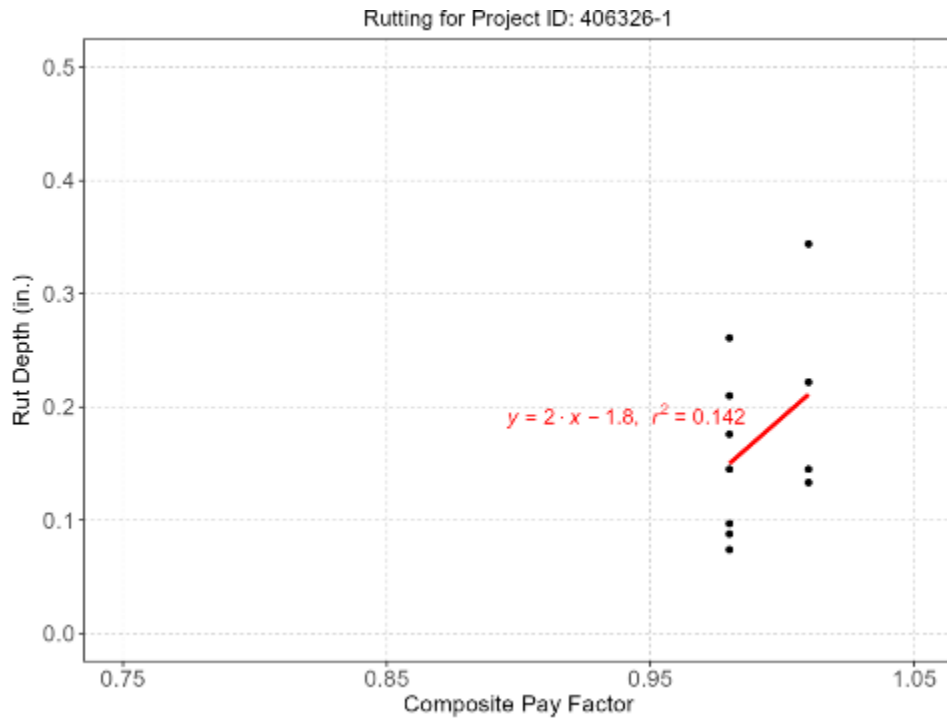


Figure C.16. Rutting vs Composite Pay Factor for Project 406326-1

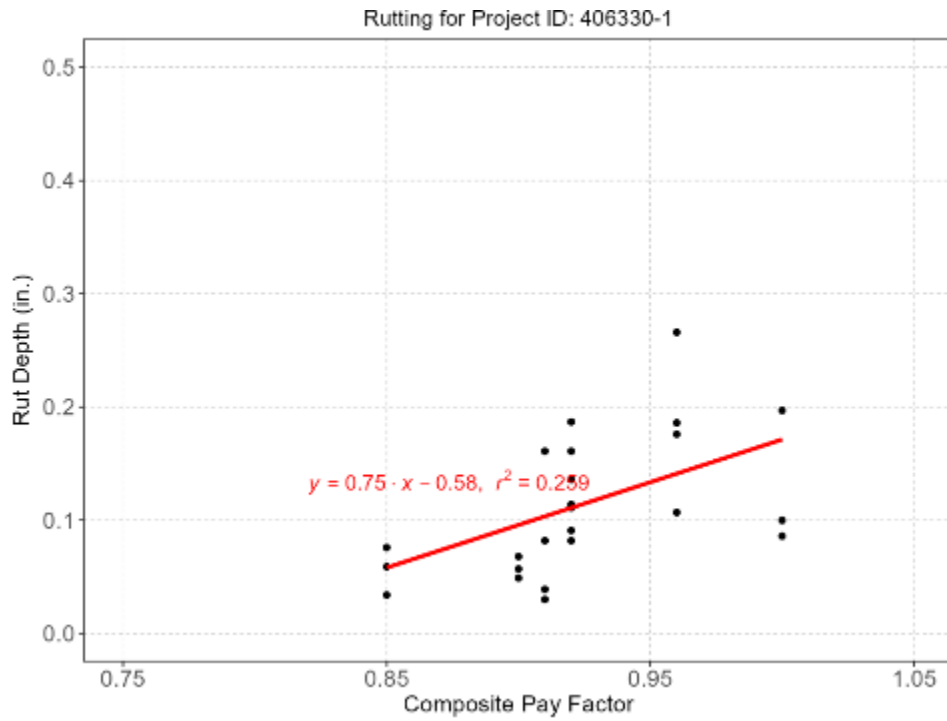


Figure C.17. Rutting vs Composite Pay Factor for Project 406330-1

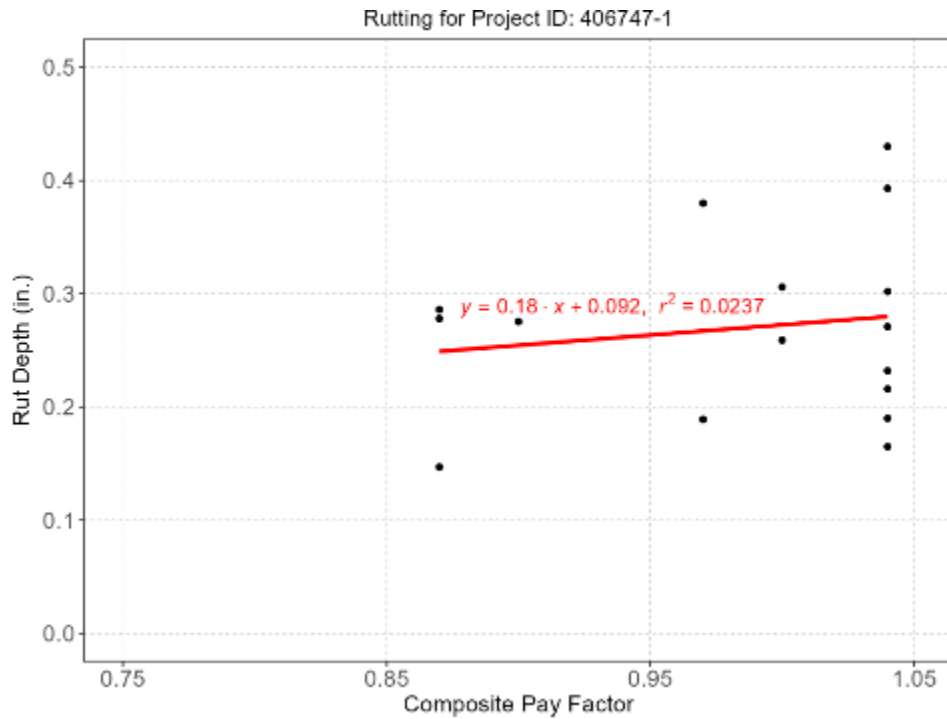


Figure C.18. Rutting vs Composite Pay Factor for Project 406747-1

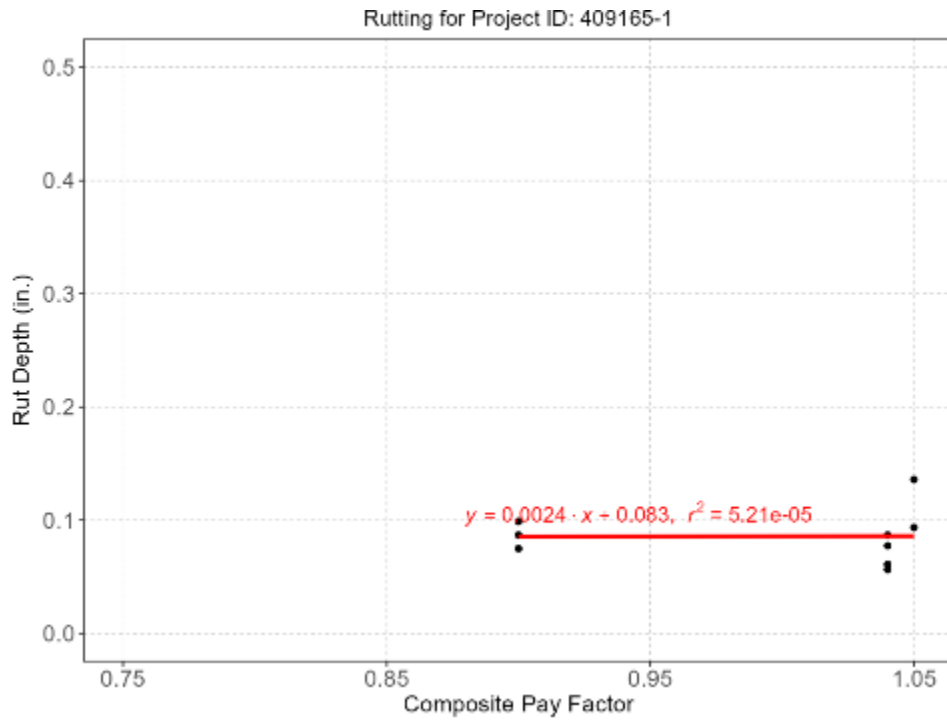


Figure C.21. Rutting vs Composite Pay Factor for Project 409165-1

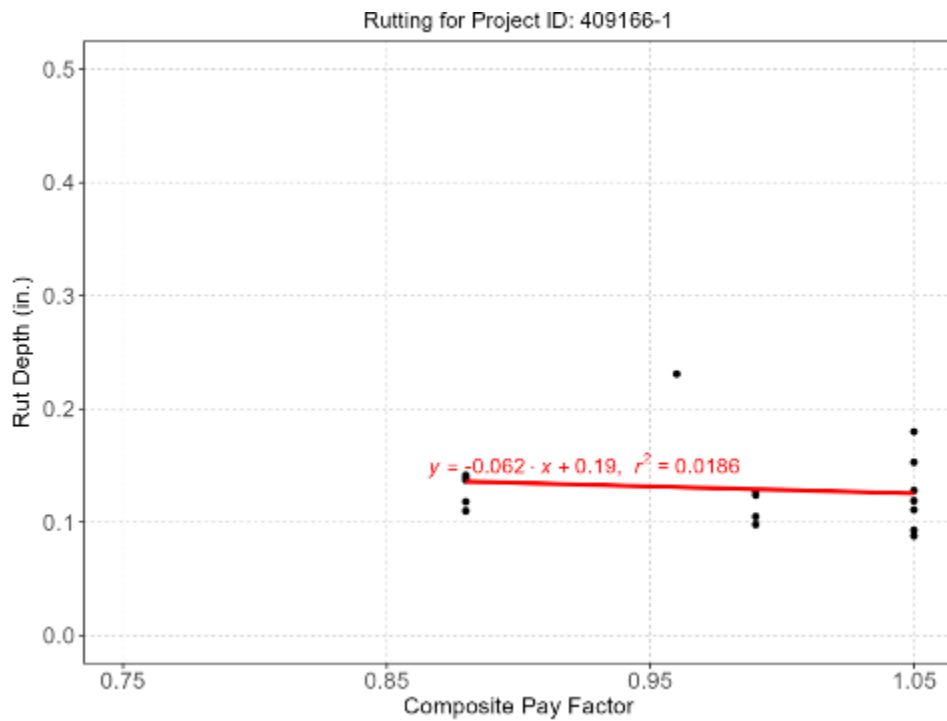


Figure C.22. Rutting vs Composite Pay Factor for Project 409166-1

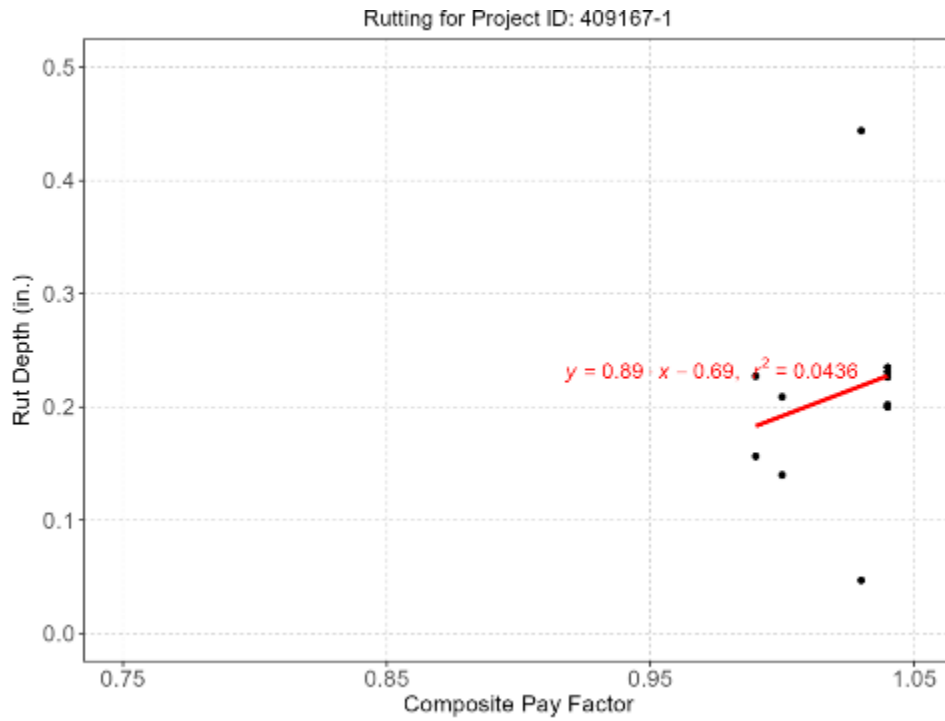


Figure C.23. Rutting vs Composite Pay Factor for Project 409167-1

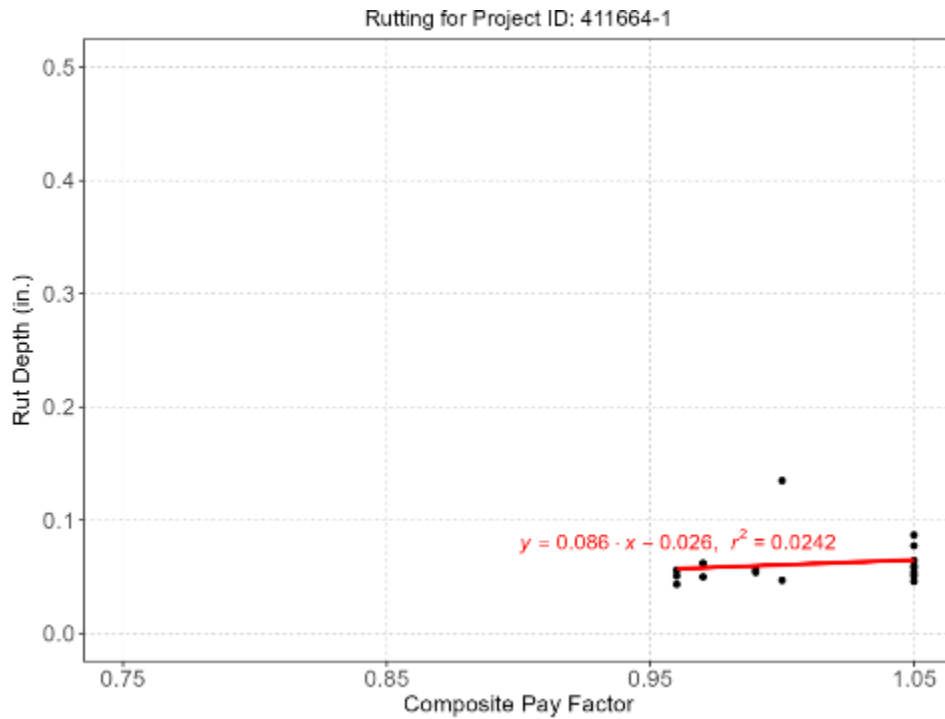


Figure C.24. Rutting vs Composite Pay Factor for Project 411664-1

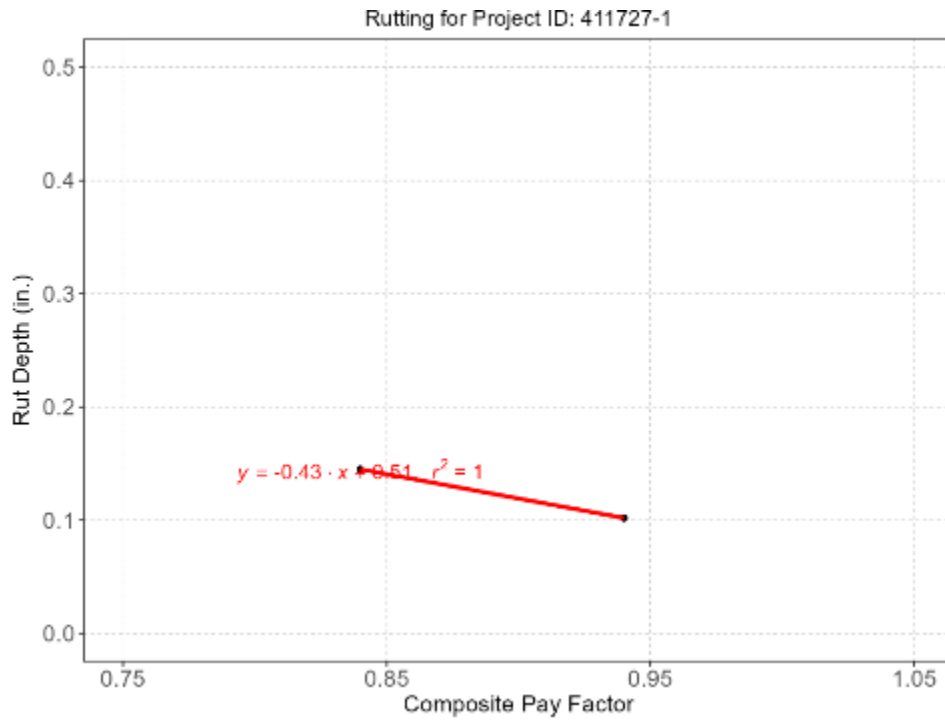


Figure C.25. Rutting vs Composite Pay Factor for Project 411727-1

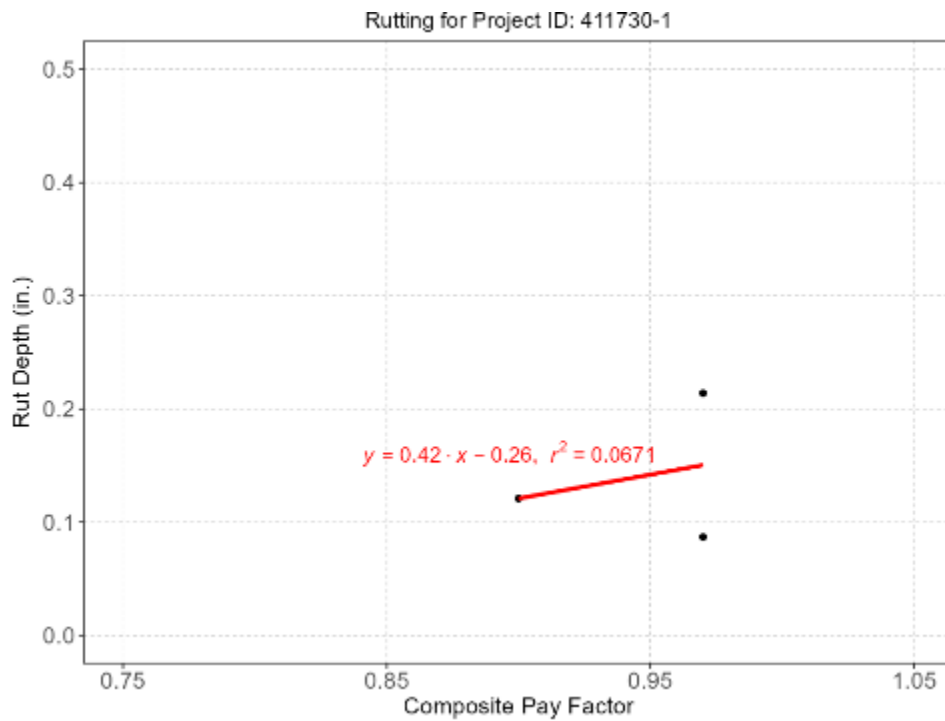


Figure C.26. Rutting vs Composite Pay Factor for Project 411730-1

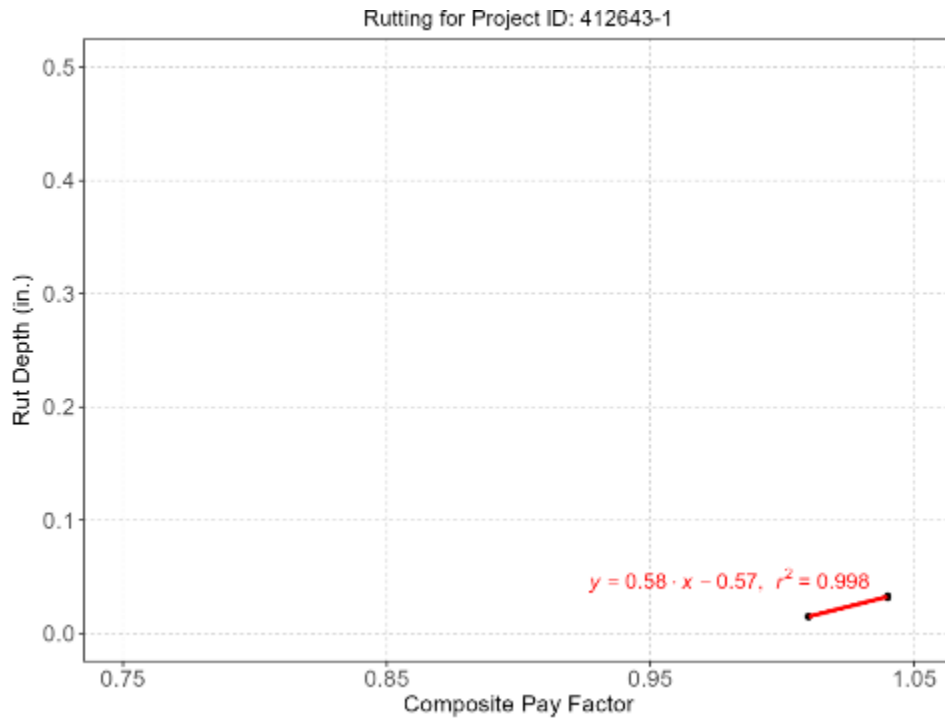


Figure C.27. Rutting vs Composite Pay Factor for Project 412643-1

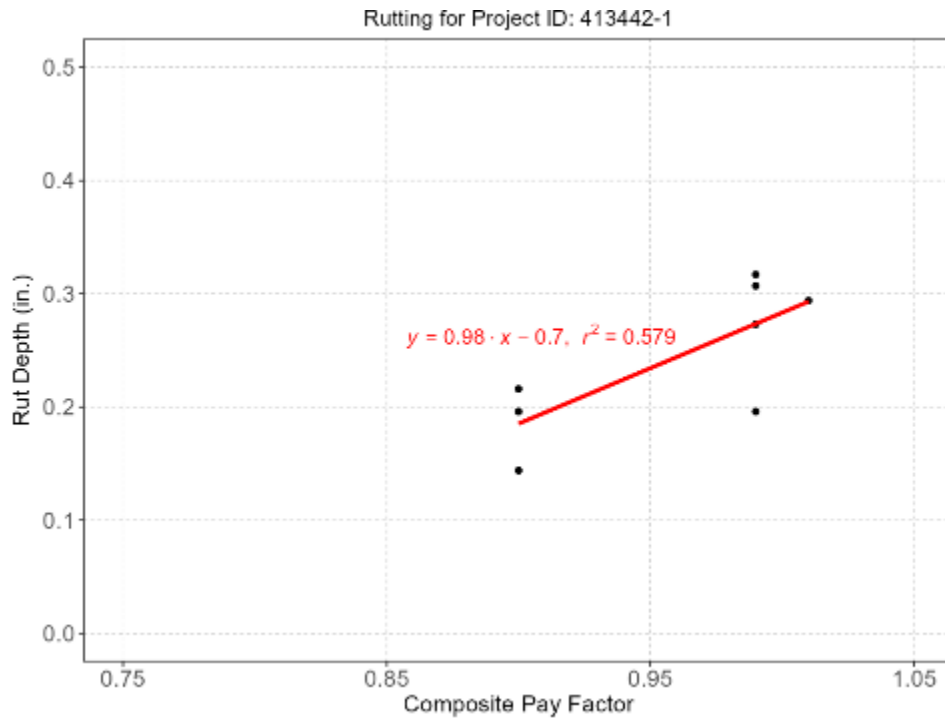


Figure C.28. Rutting vs Composite Pay Factor for Project 413442-1

**APPENDIX D: PROJECT LEVEL CORRELATIONS CPF VS
RAVELING FOR DENSE GRADED MIXTURES**

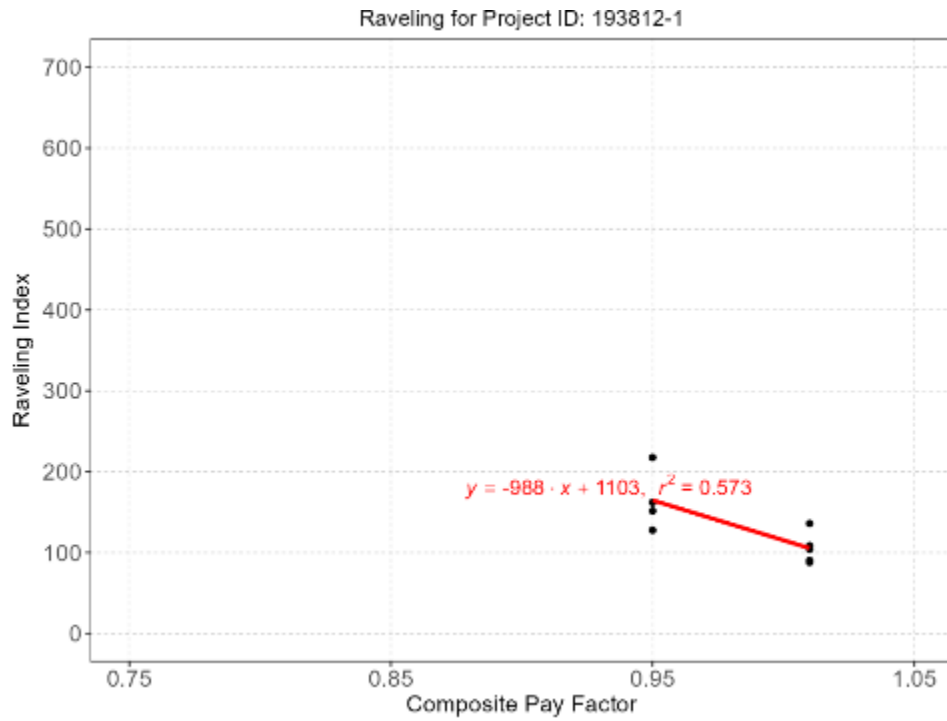


Figure D.1. Raveling vs Composite Pay Factor for Project 193812-1

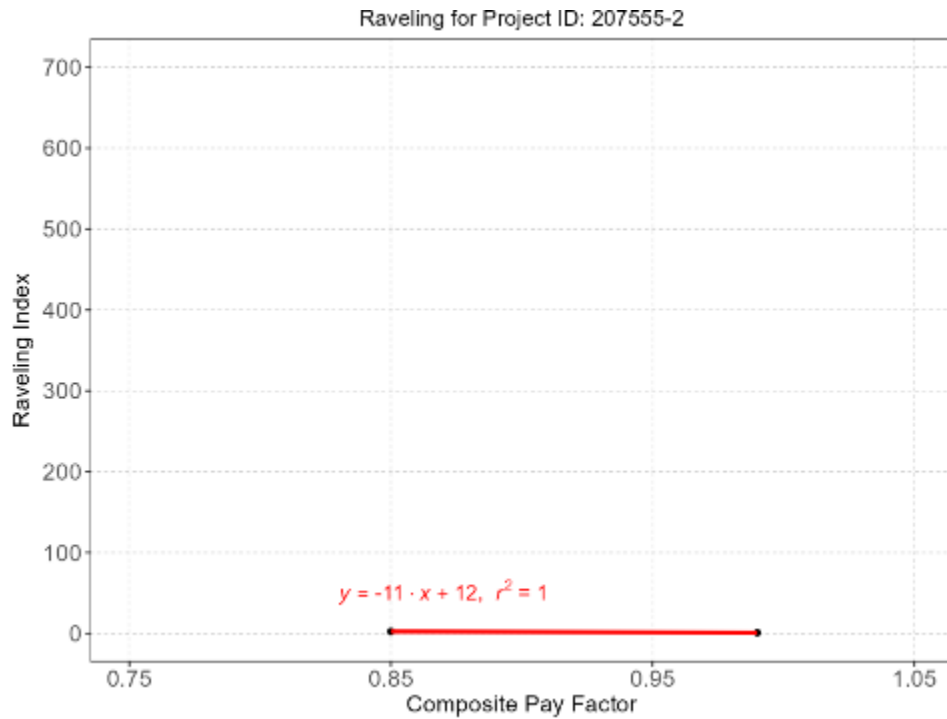


Figure D.2. Raveling vs Composite Pay Factor for Project 207555-2

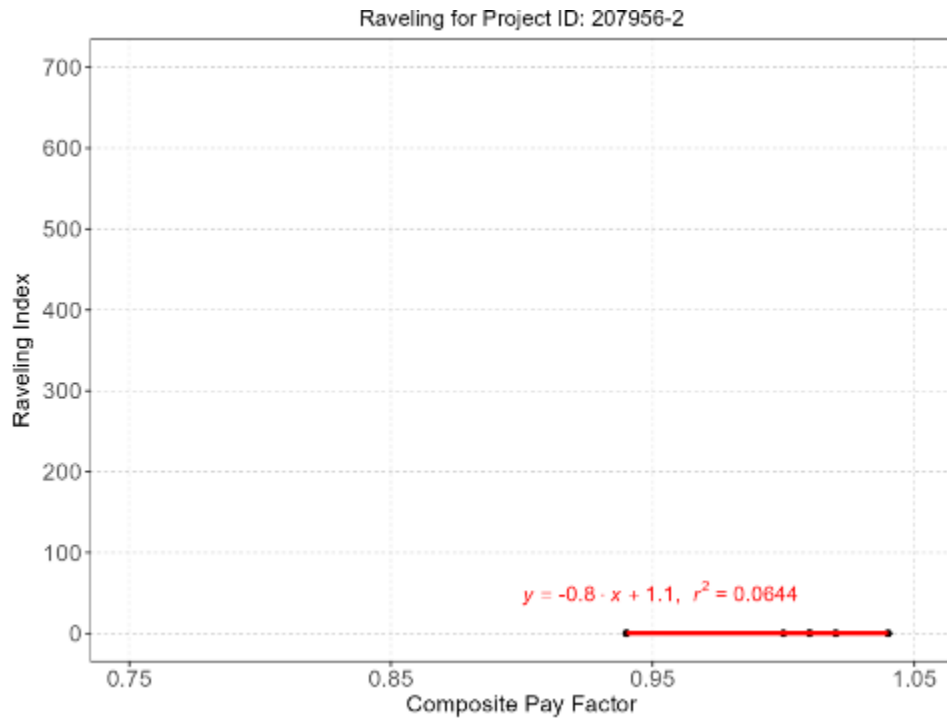


Figure D.3. Raveling vs Composite Pay Factor for Project 207956-2

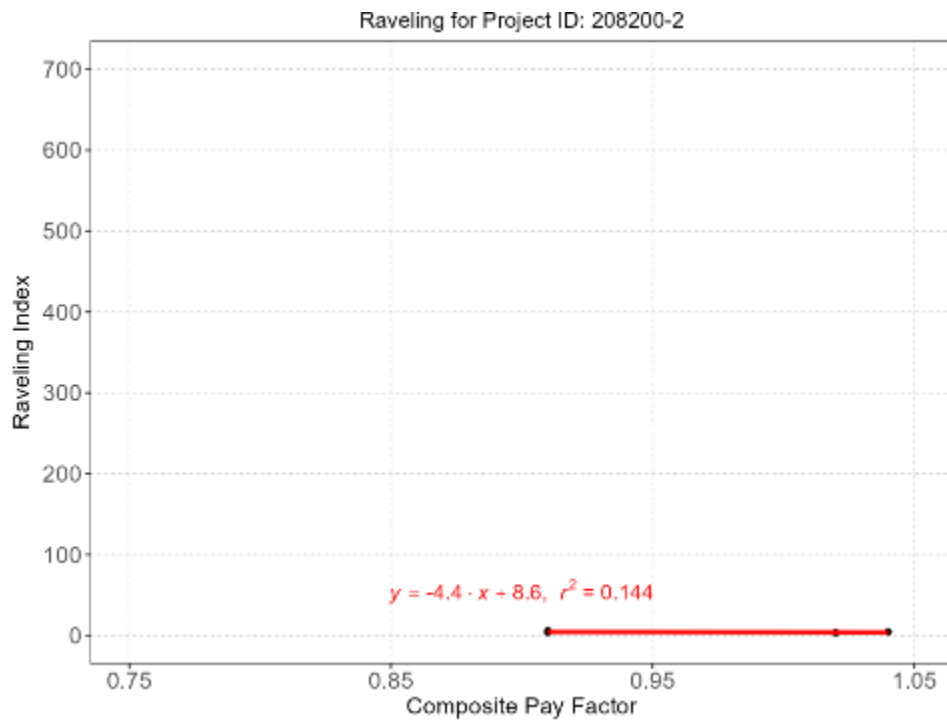


Figure D.4. Raveling vs Composite Pay Factor for Project 208200-2

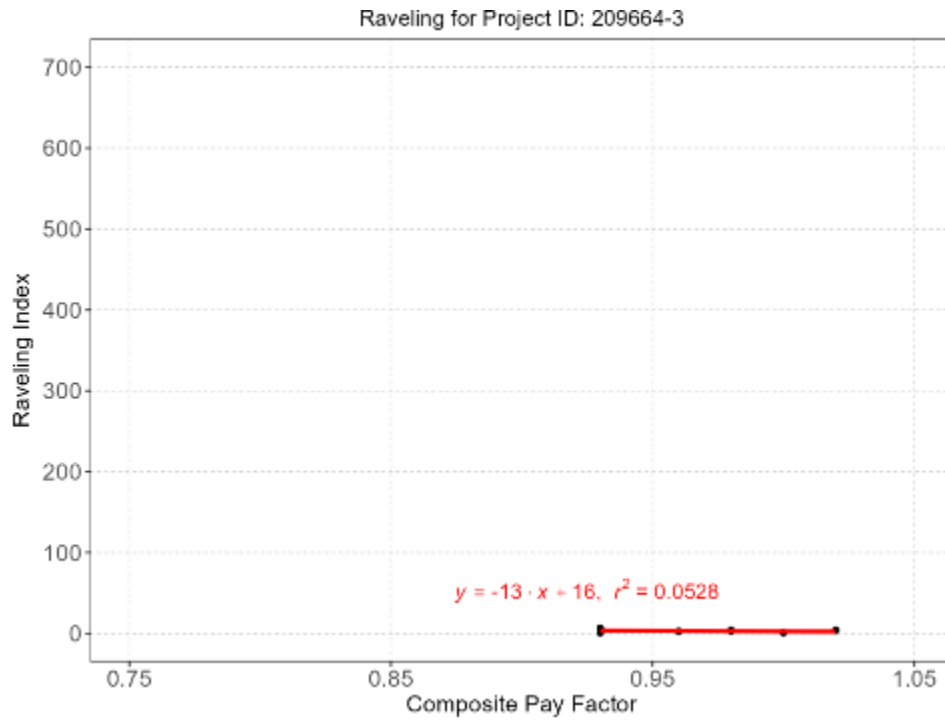


Figure D.5. Raveling vs Composite Pay Factor for Project 209664-3

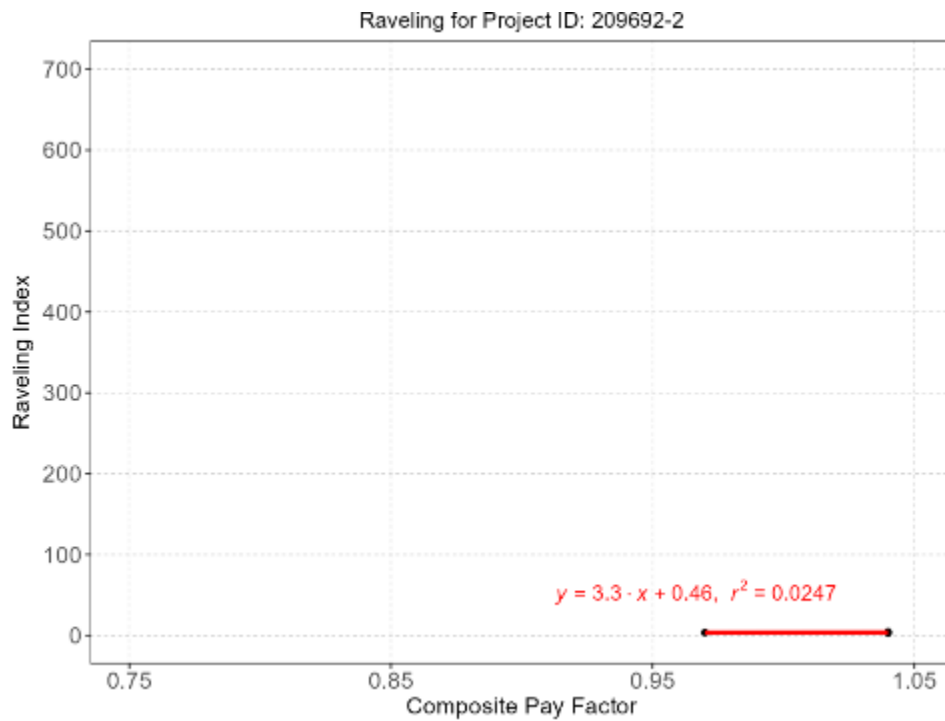


Figure D.6. Raveling vs Composite Pay Factor for Project 209692-2

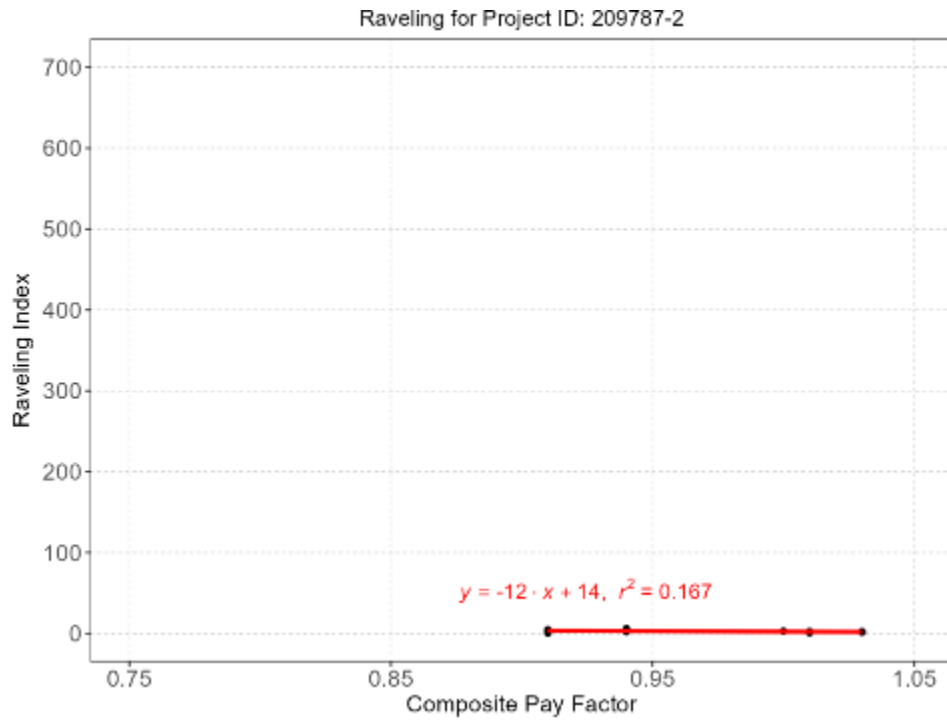


Figure D.7. Raveling vs Composite Pay Factor for Project 209787-2

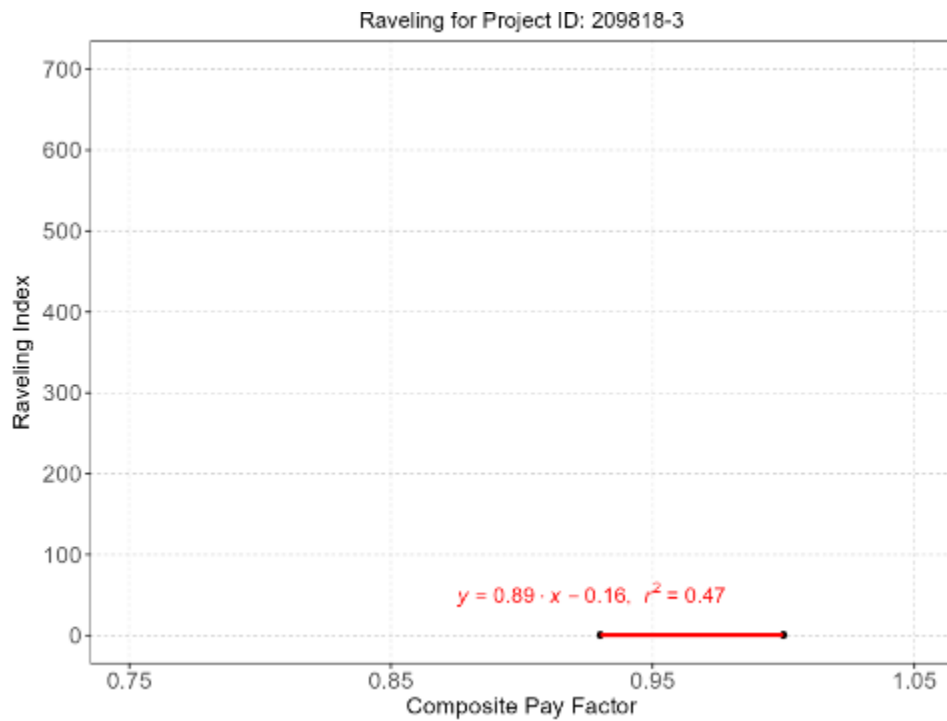


Figure D.8. Raveling vs Composite Pay Factor for Project 209818-3

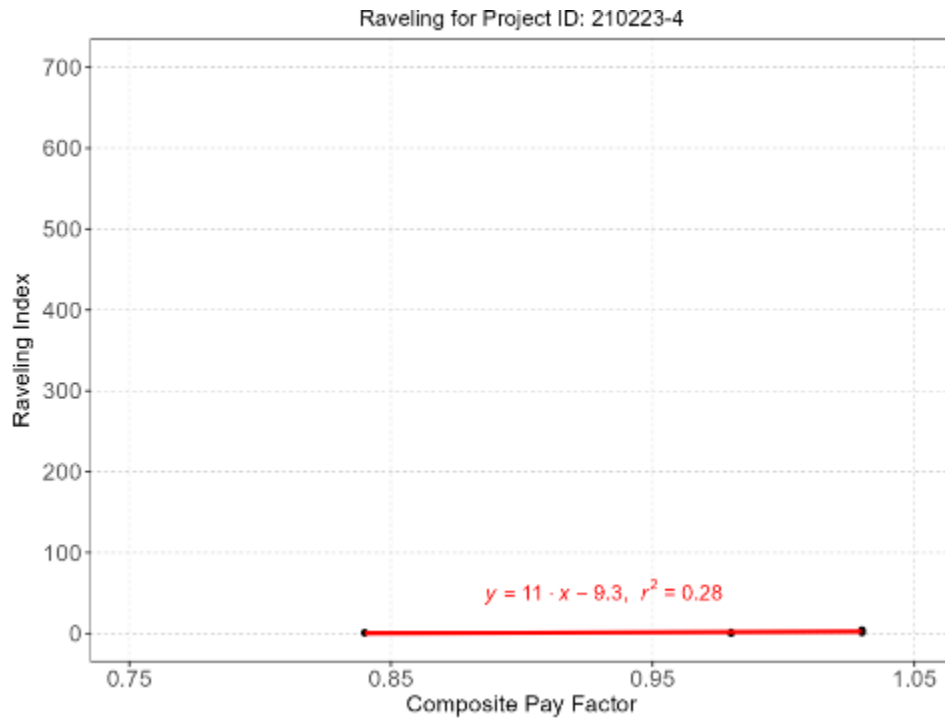


Figure D.9. Raveling vs Composite Pay Factor for Project 210223-4

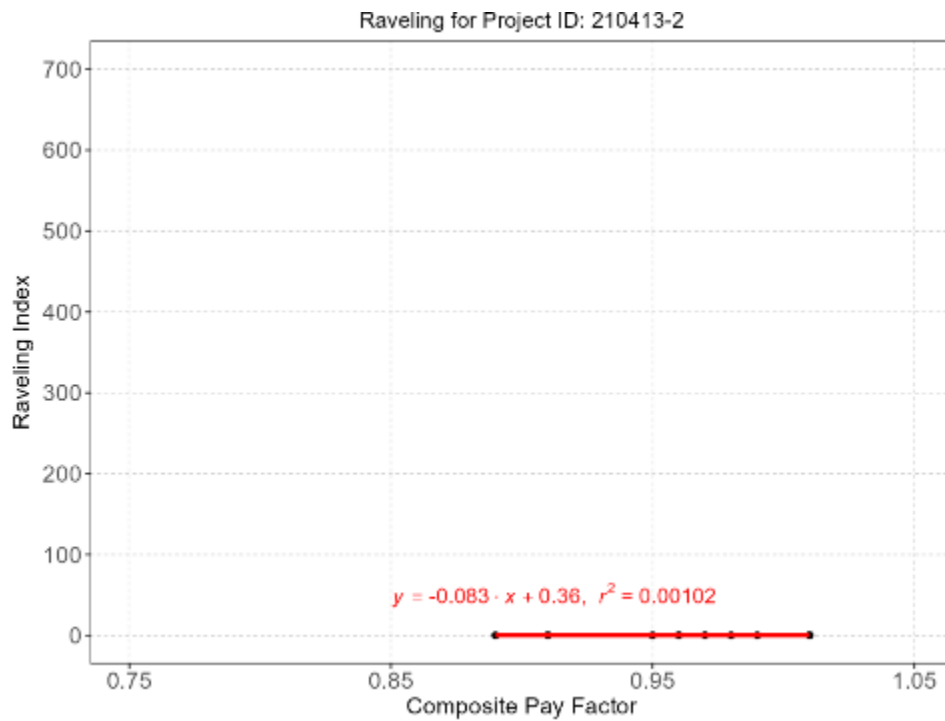


Figure D.10. Raveling vs Composite Pay Factor for Project 210413-2

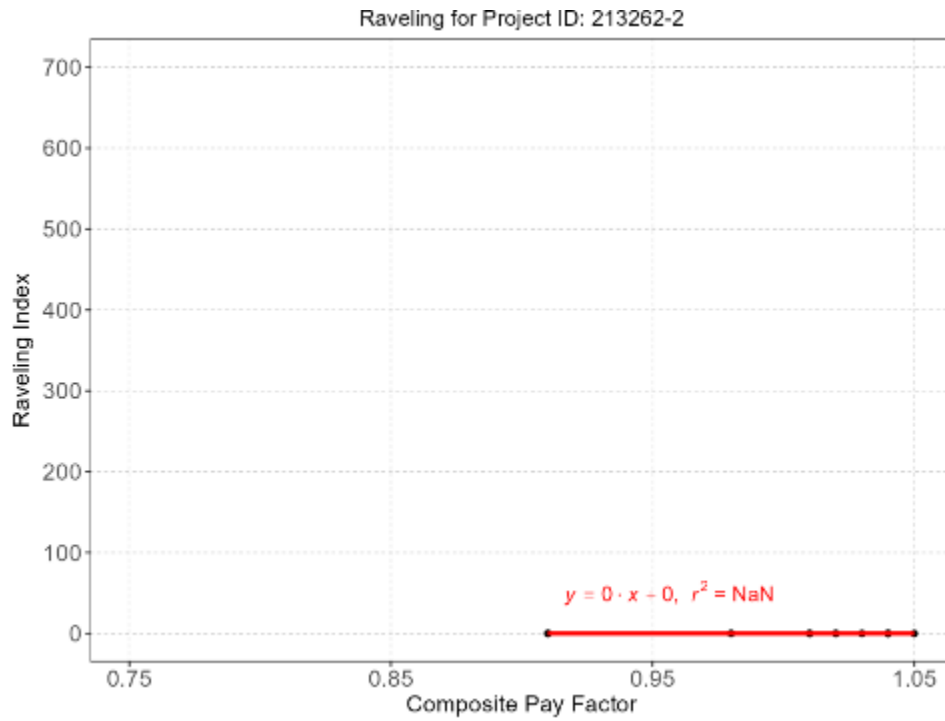


Figure D.11. Raveling vs Composite Pay Factor for Project 213262-2

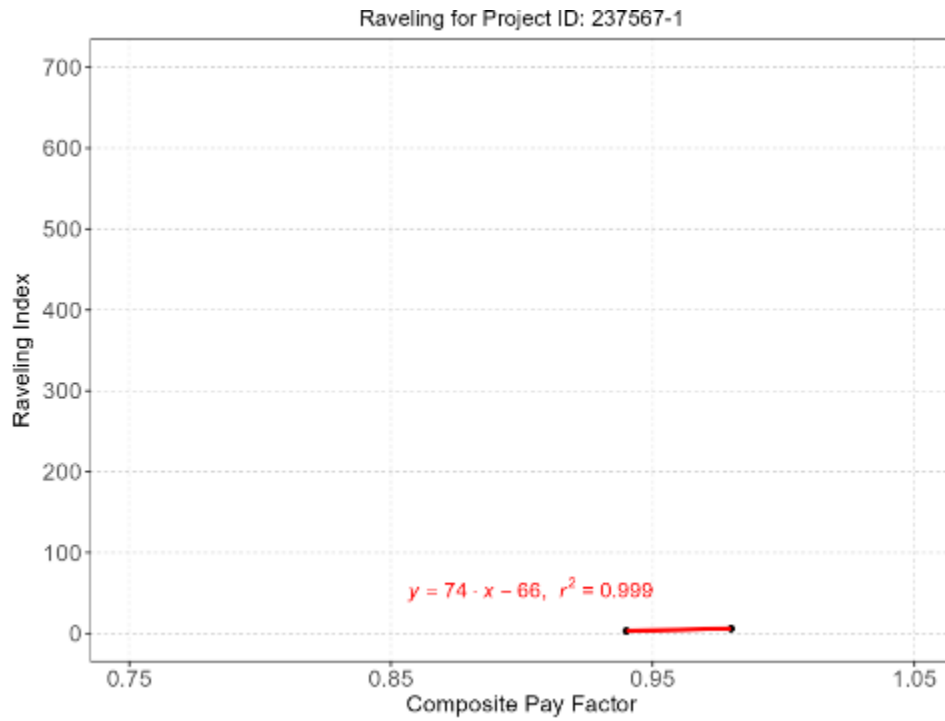


Figure D.12. Raveling vs Composite Pay Factor for Project 237567-1

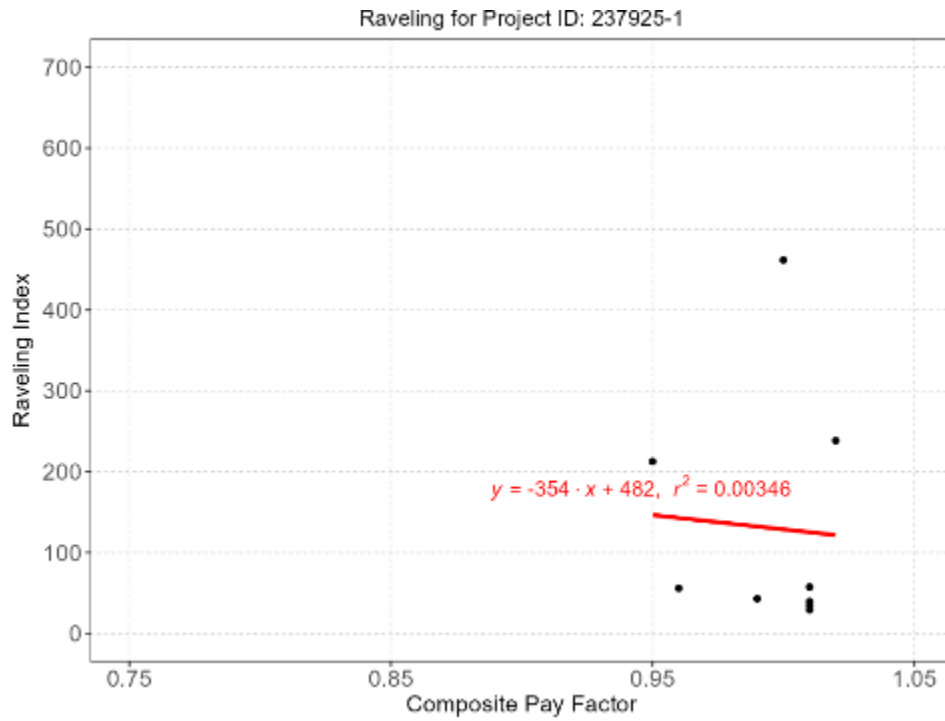


Figure D.13. Raveling vs Composite Pay Factor for Project 237925-1

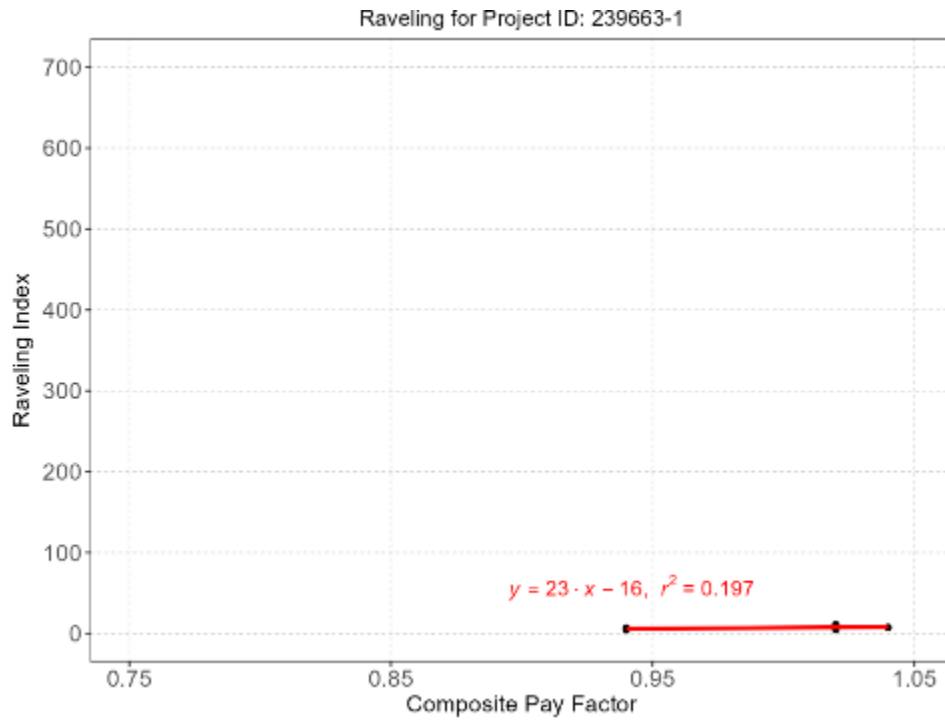


Figure D.14. Raveling vs Composite Pay Factor for Project 239663-1

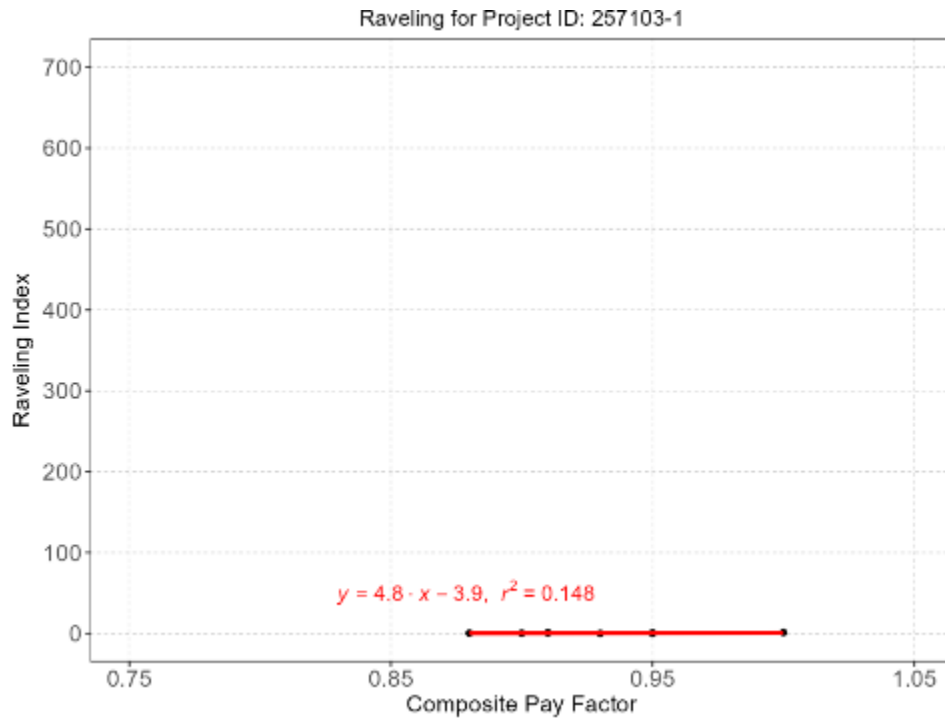


Figure D.15. Raveling vs Composite Pay Factor for Project 257103-1

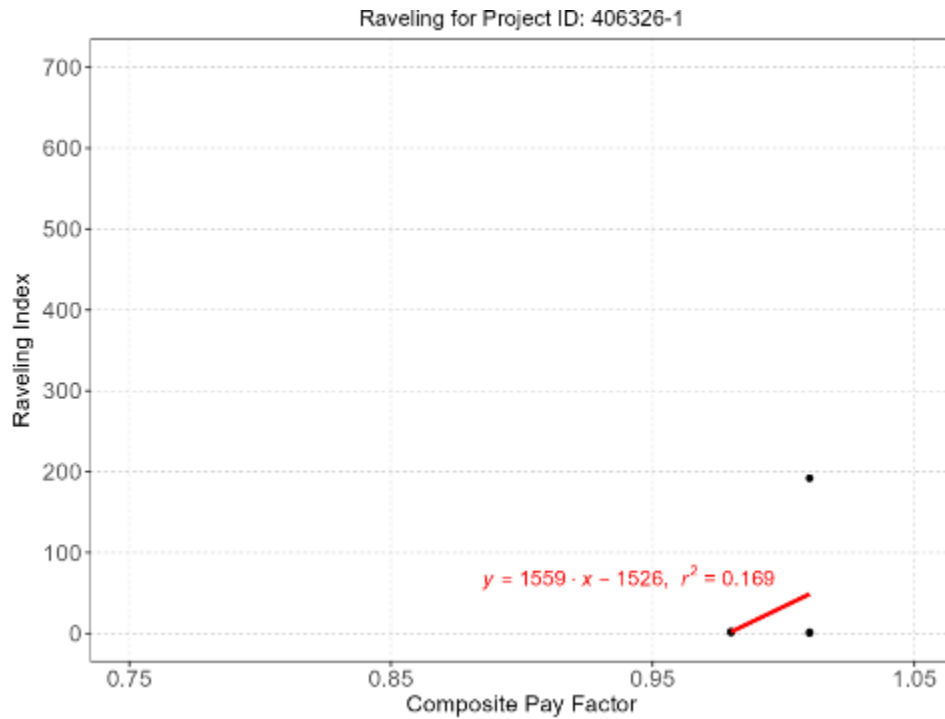


Figure D.16. Raveling vs Composite Pay Factor for Project 406326-1

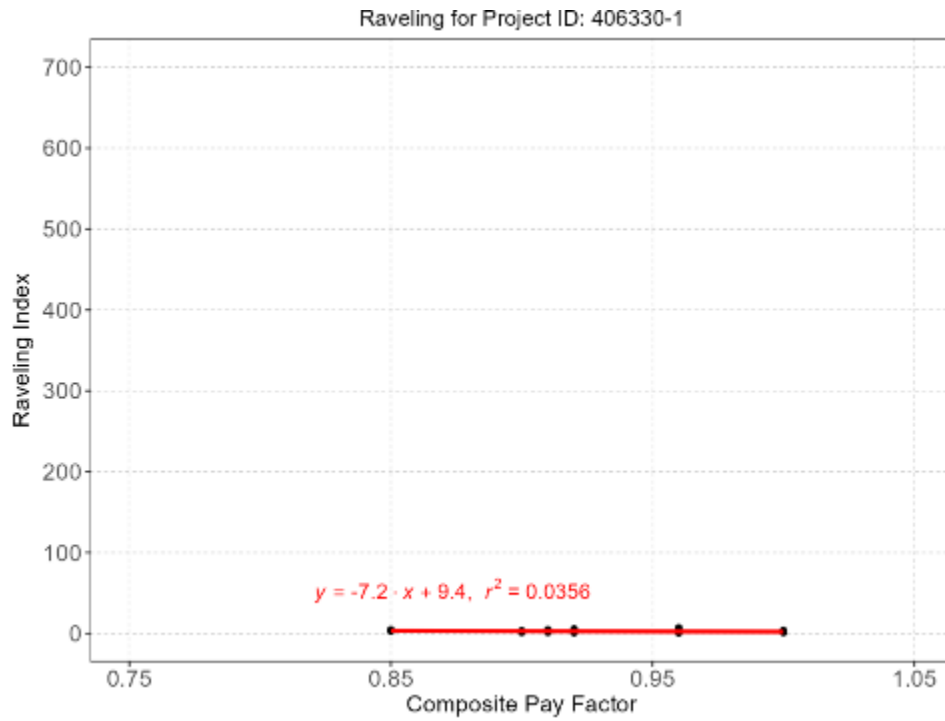


Figure D.17. Raveling vs Composite Pay Factor for Project 406330-1

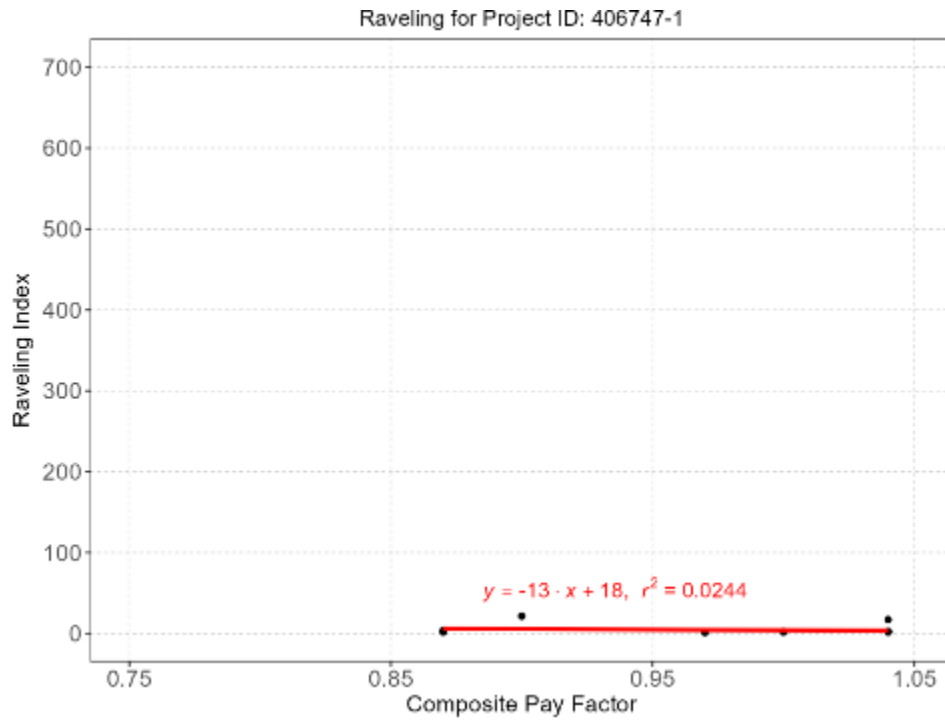


Figure D.18. Raveling vs Composite Pay Factor for Project 406747-1

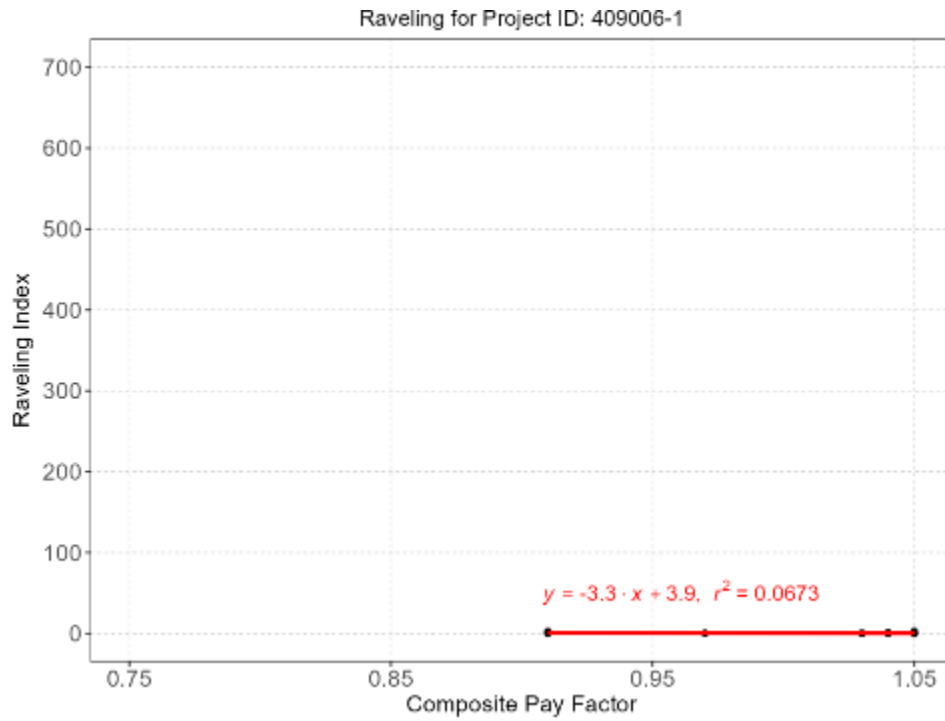


Figure D.19. Raveling vs Composite Pay Factor for Project 409006-1

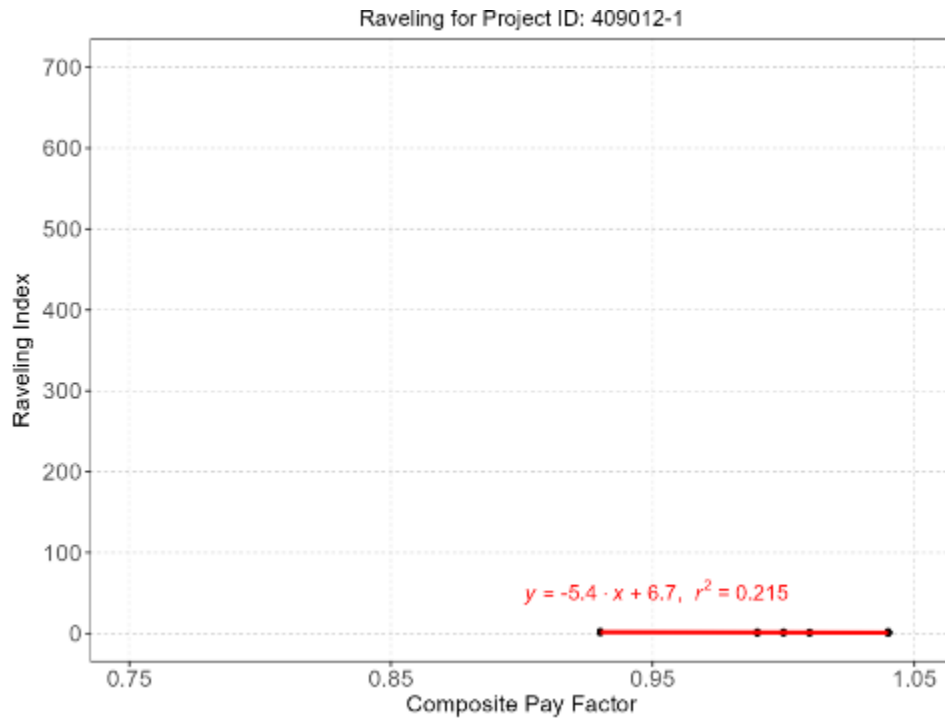


Figure D.20. Raveling vs Composite Pay Factor for Project 409012-1

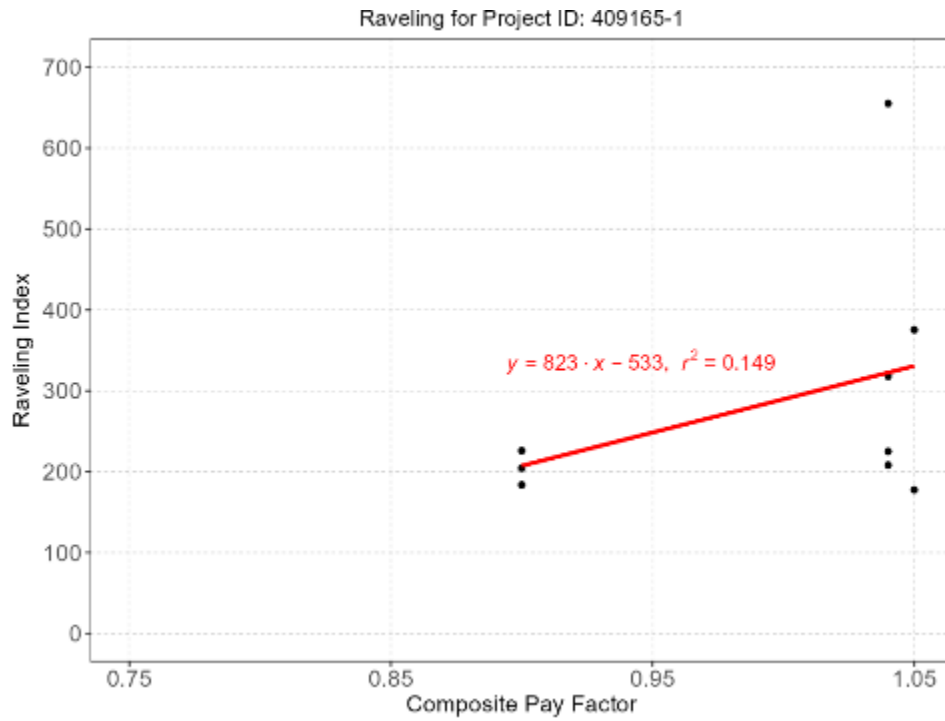


Figure D.21. Raveling vs Composite Pay Factor for Project 409165-1

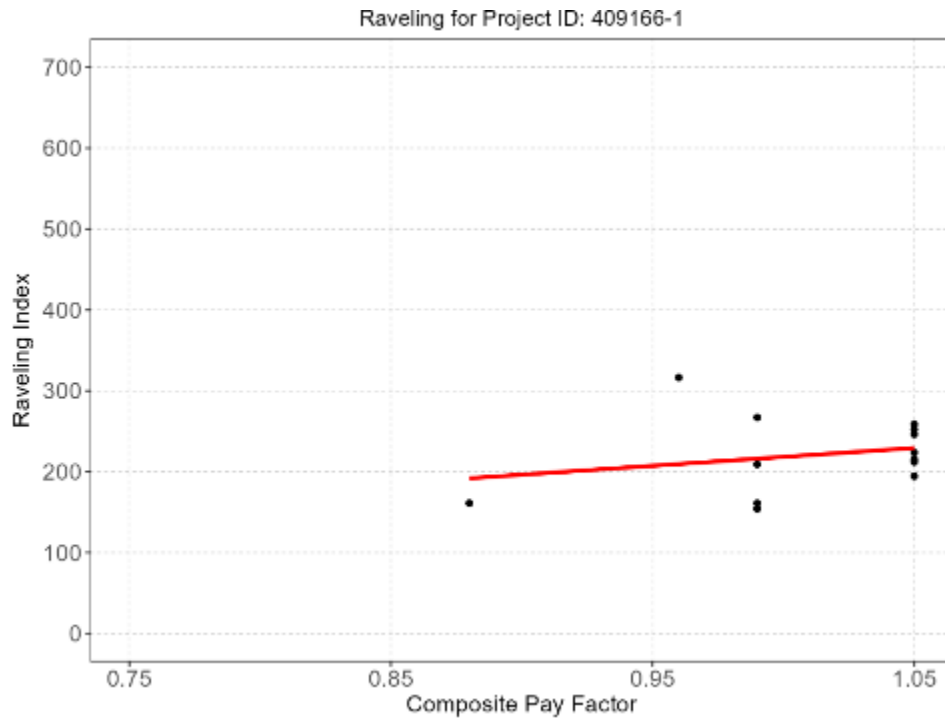


Figure D.22. Raveling vs Composite Pay Factor for Project 409166-1

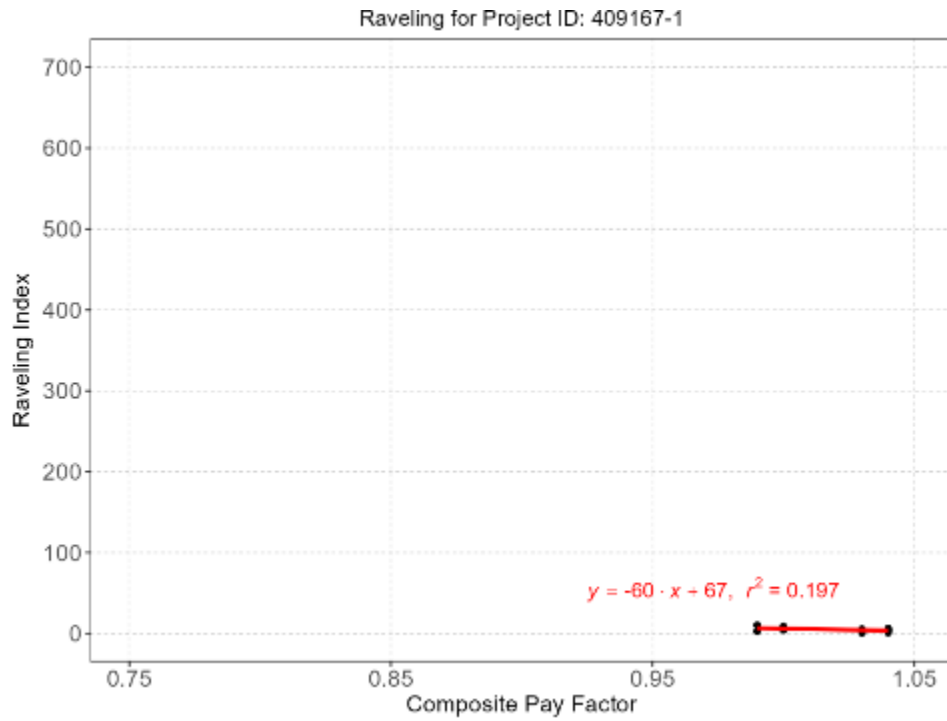


Figure D.23. Raveling vs Composite Pay Factor for Project 409167-1

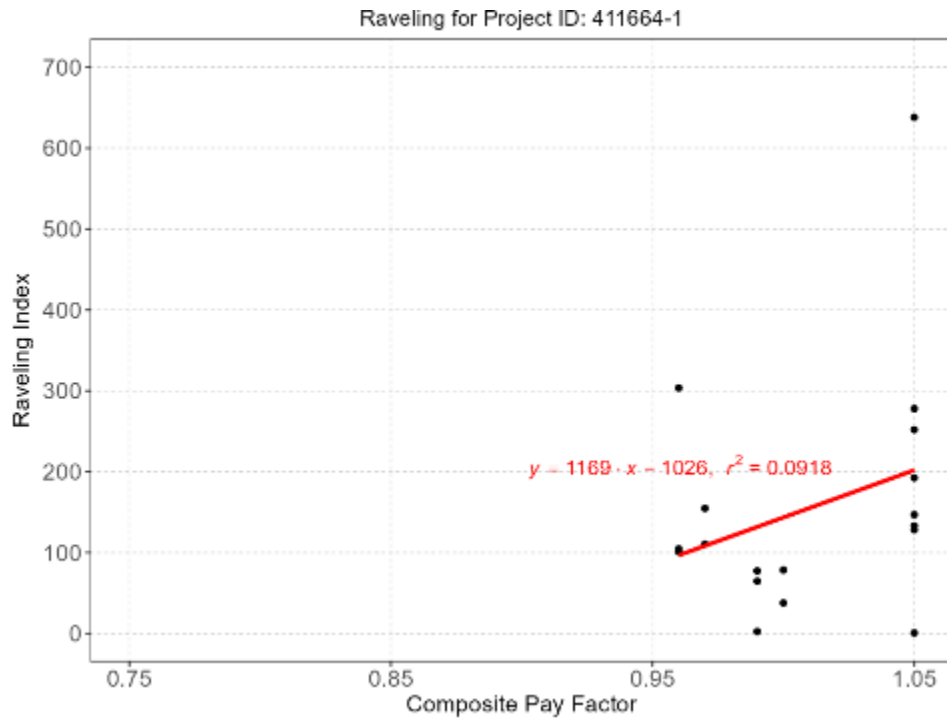


Figure D.24. Raveling vs Composite Pay Factor for Project 411664-1

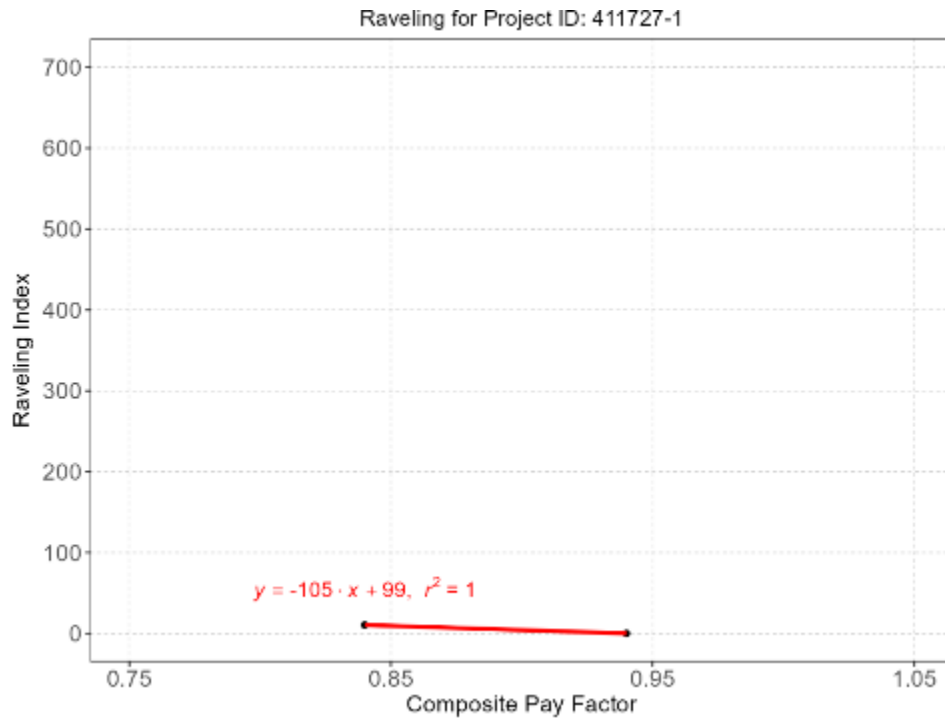


Figure D.25. Raveling vs Composite Pay Factor for Project 411727-1

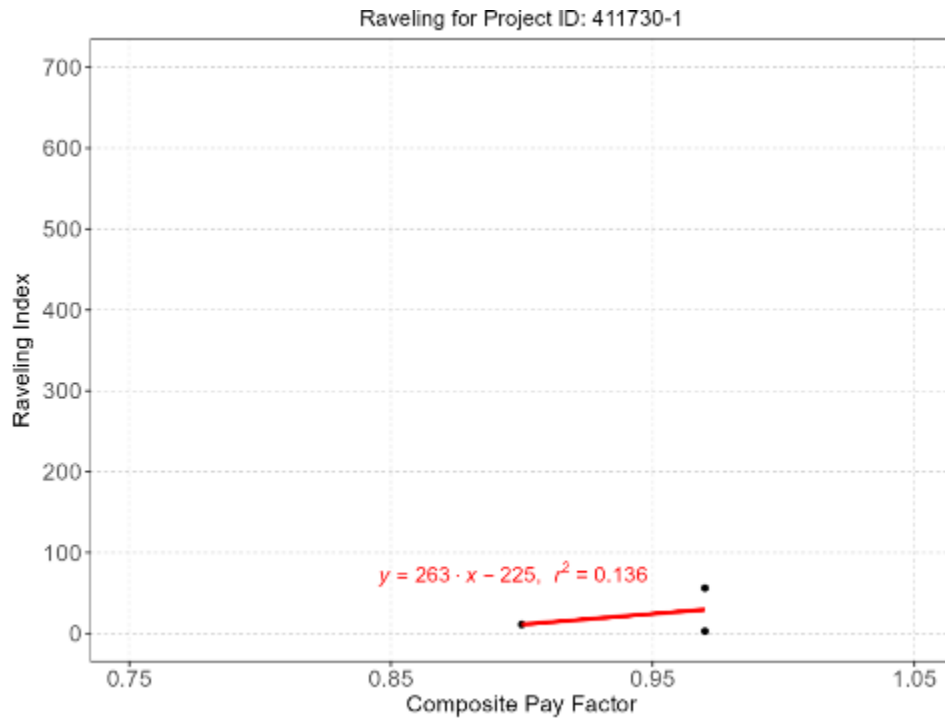


Figure D.26. Raveling vs Composite Pay Factor for Project 411730-1

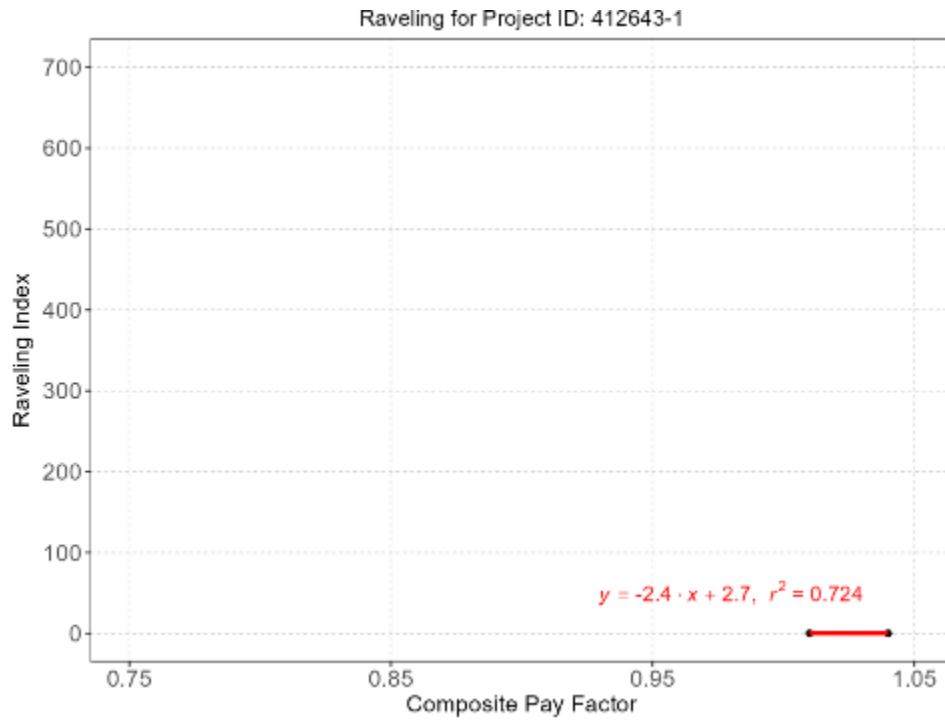


Figure D.27. Raveling vs Composite Pay Factor for Project 412643-1

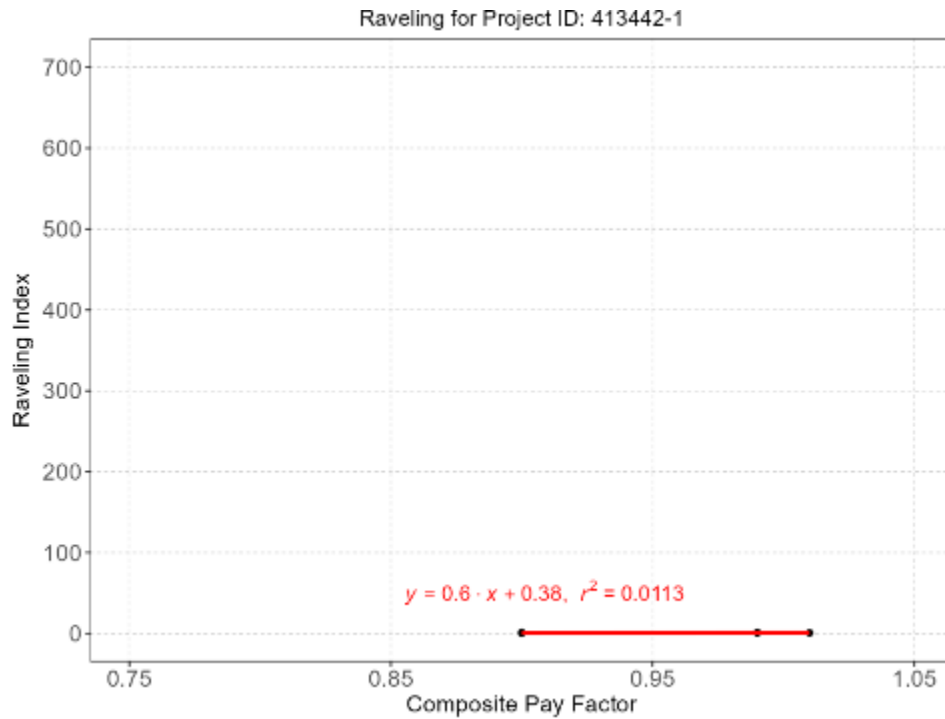


Figure D.28. Raveling vs Composite Pay Factor for Project 413442-1

**APPENDIX E: PROJECT LEVEL CORRELATIONS CPF VS
CRACKING FOR OPEN GRADED MIXTURES**

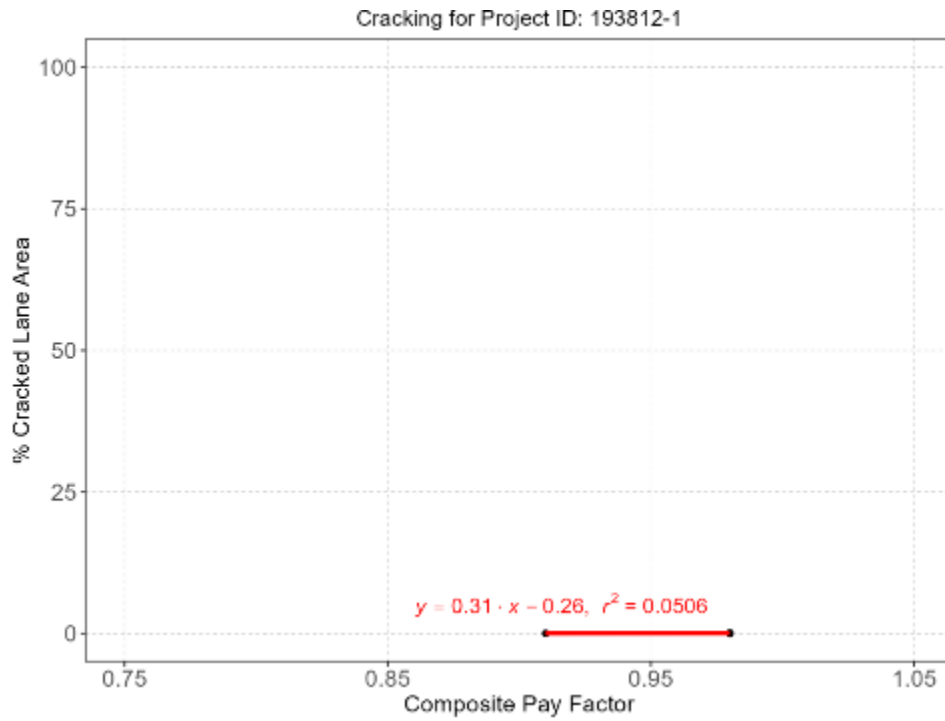


Figure E.1. Total Cracking vs Composite Pay Factor for Project 193812-1

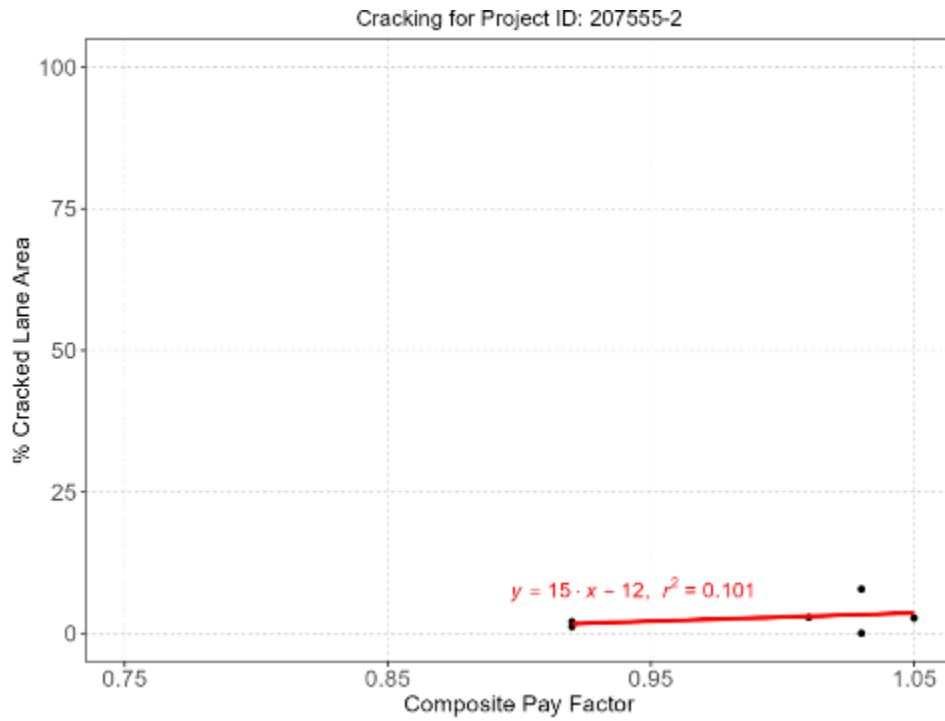


Figure E.2. Total Cracking vs Composite Pay Factor for Project 207555-2

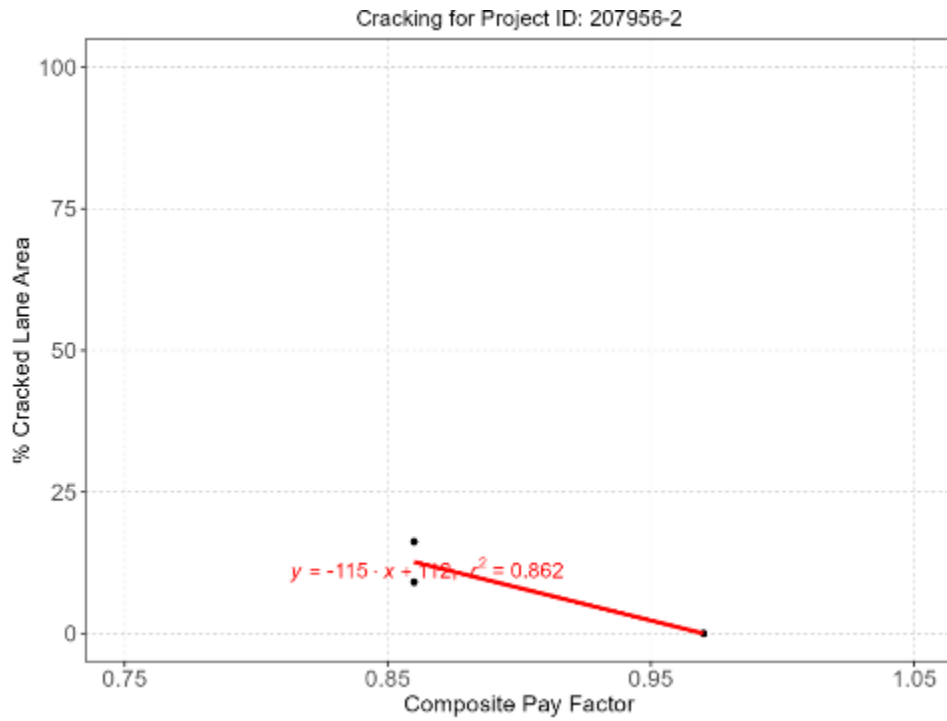


Figure E.3. Total Cracking vs Composite Pay Factor for Project 207956-2

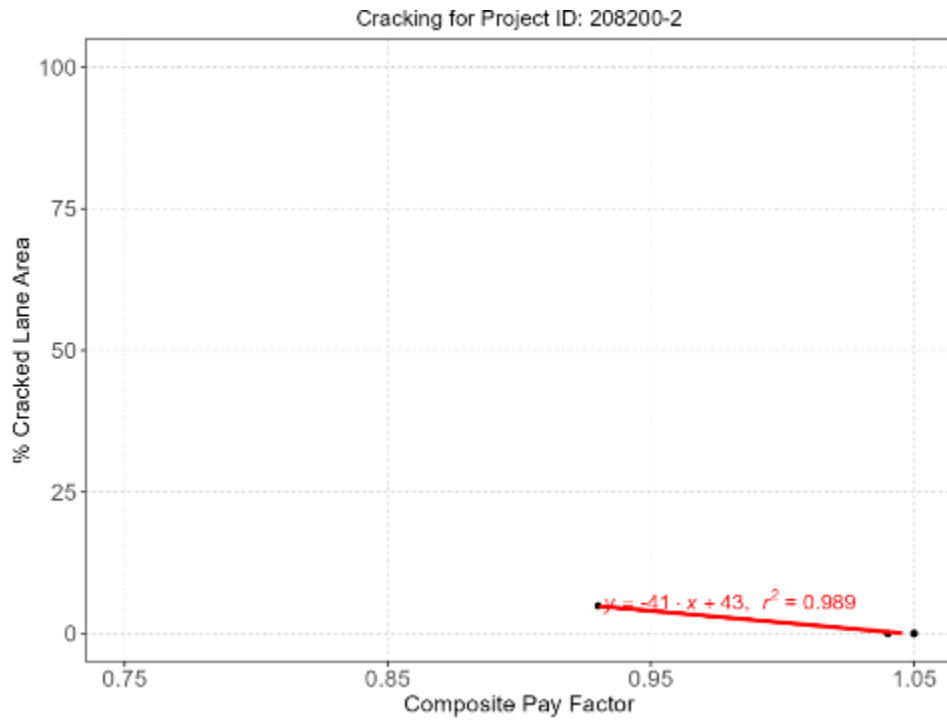


Figure E.4. Total Cracking vs Composite Pay Factor for Project 208200-2

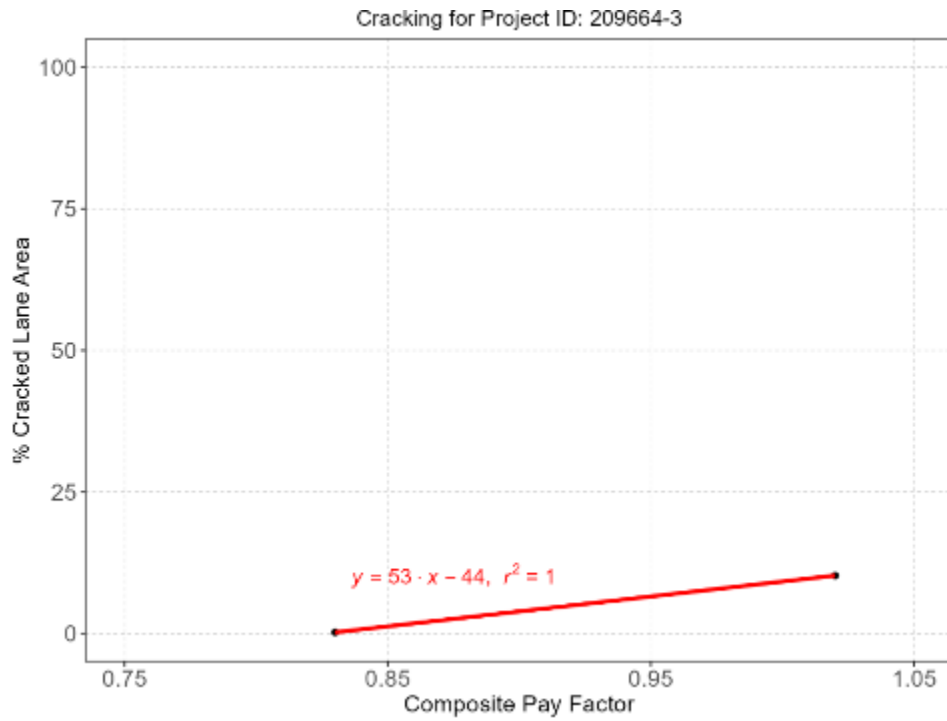


Figure E.5. Total Cracking vs Composite Pay Factor for Project 209664-3

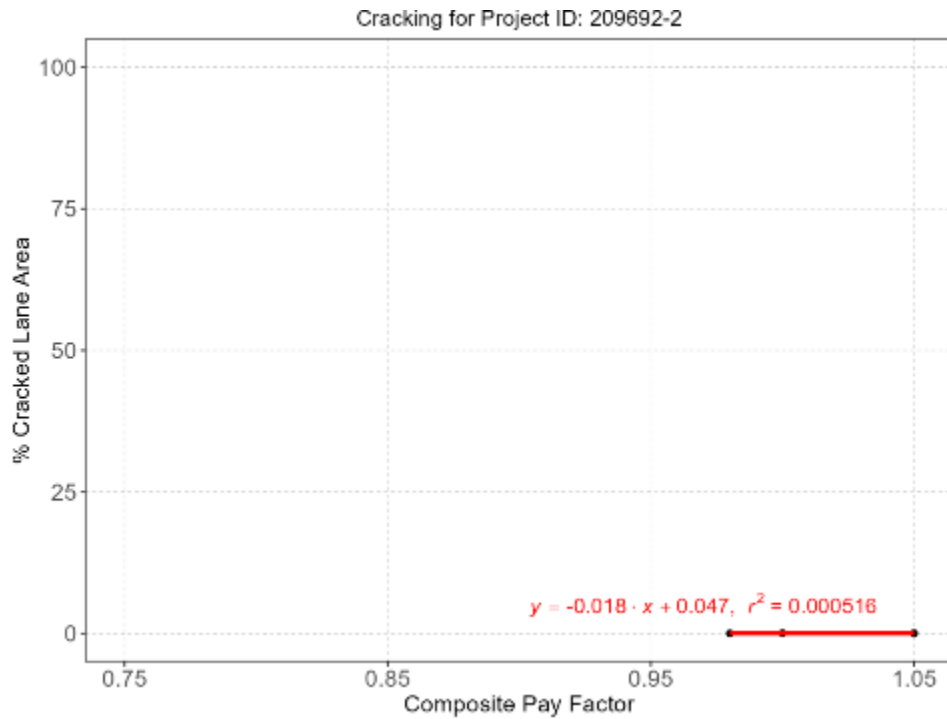


Figure E.6. Total Cracking vs Composite Pay Factor for Project 209692-2

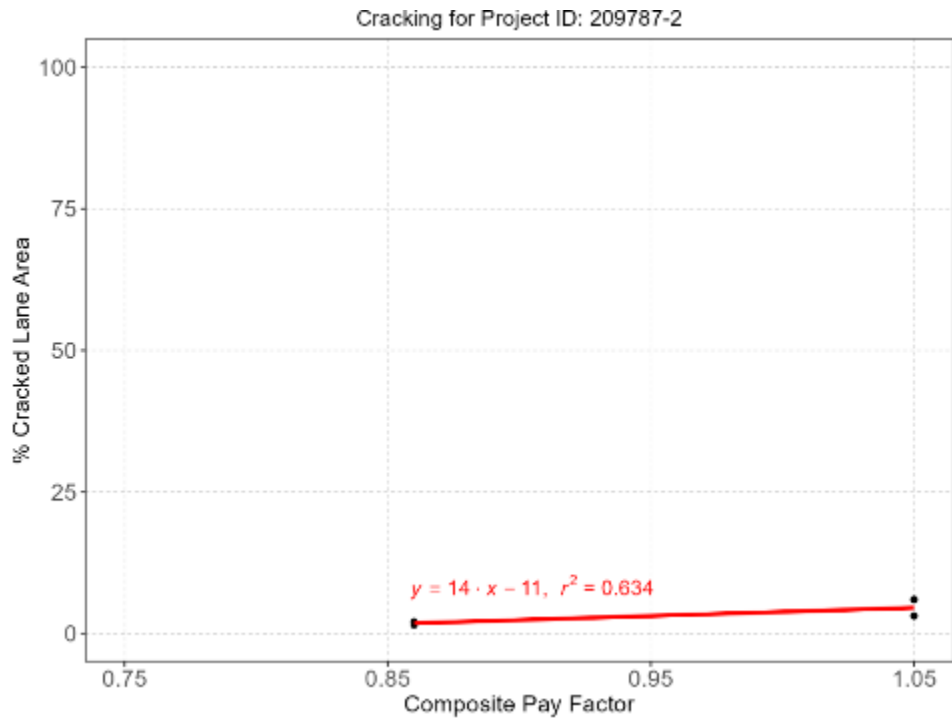


Figure E.7. Total Cracking vs Composite Pay Factor for Project 209767-2

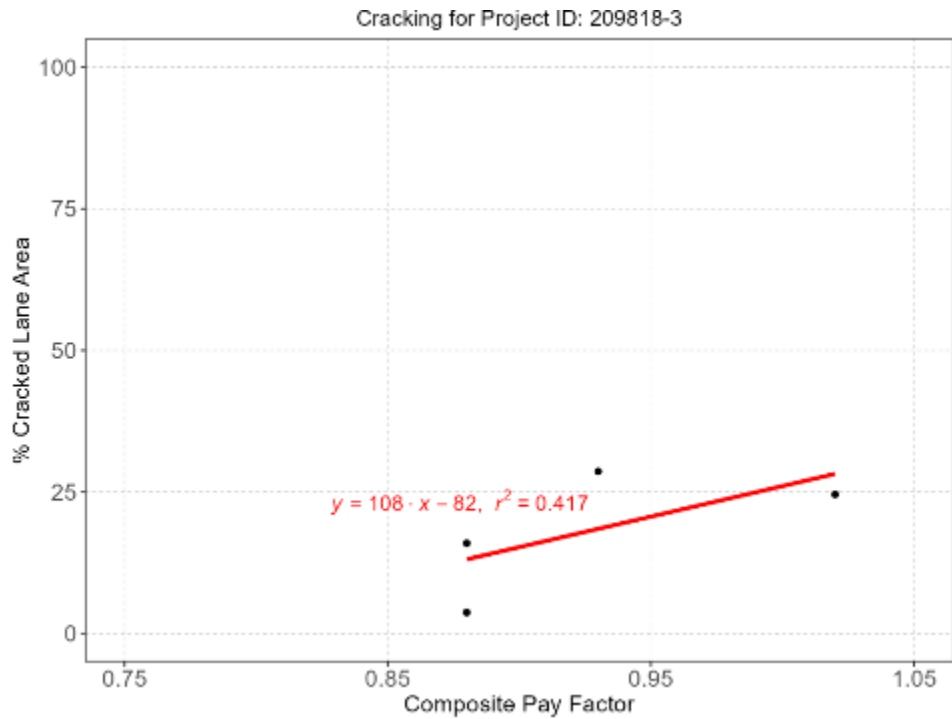


Figure E.8. Total Cracking vs Composite Pay Factor for Project 209818-3

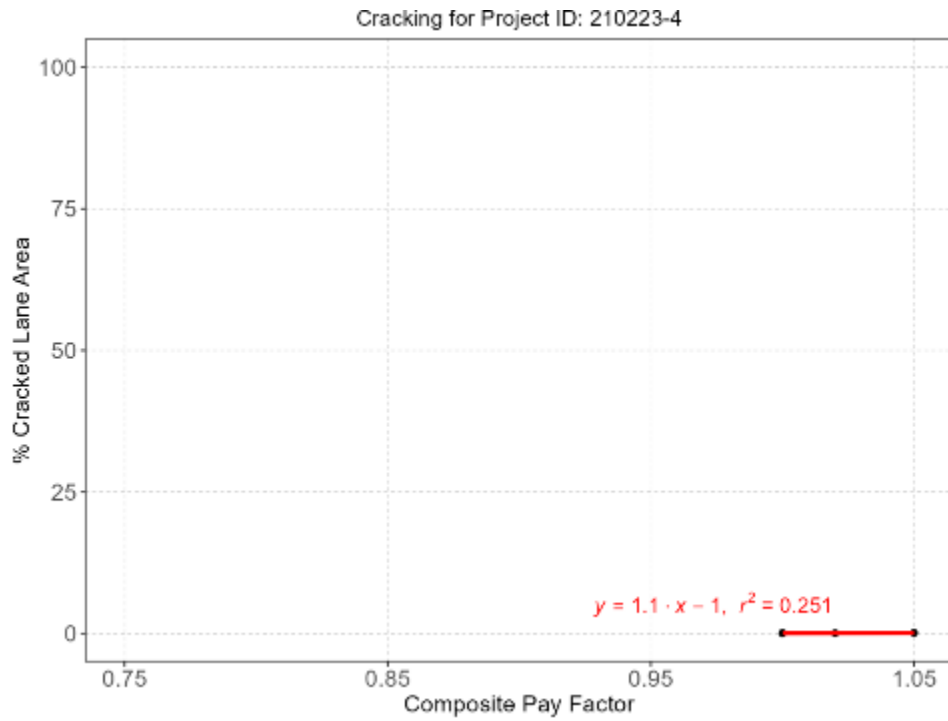


Figure E.9. Total Cracking vs Composite Pay Factor for Project 210223-4

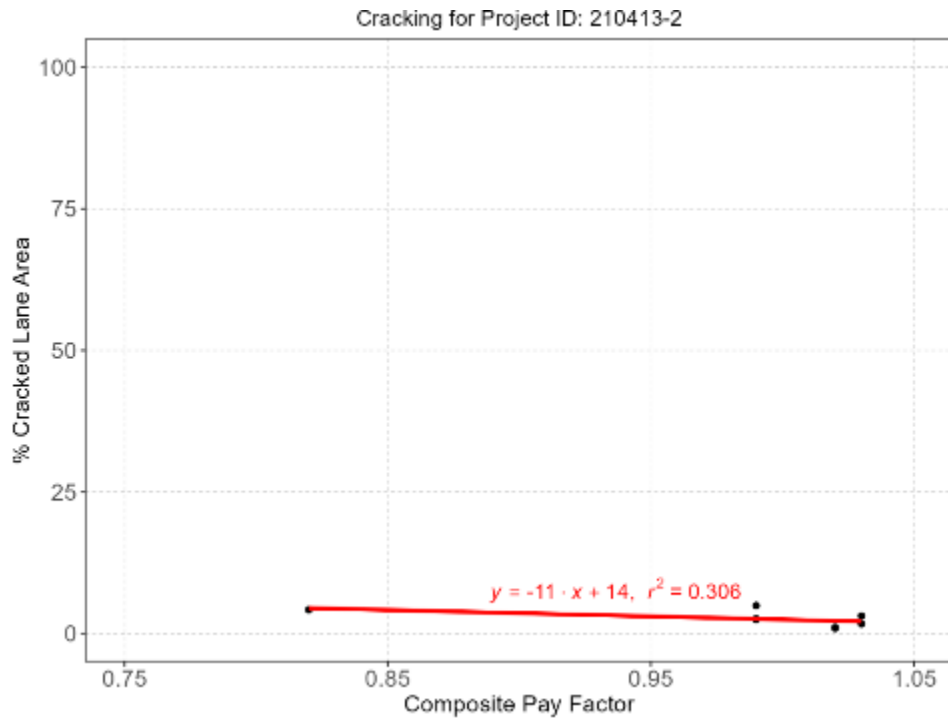


Figure E.10. Total Cracking vs Composite Pay Factor for Project 210413-2

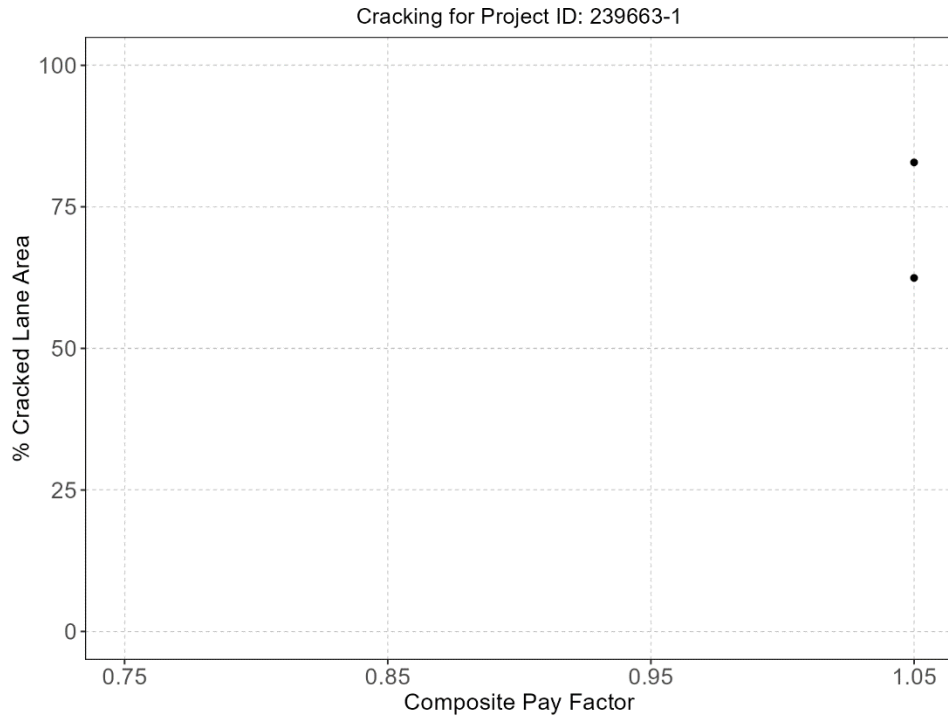


Figure E.11. Total Cracking vs Composite Pay Factor for Project 239663-1

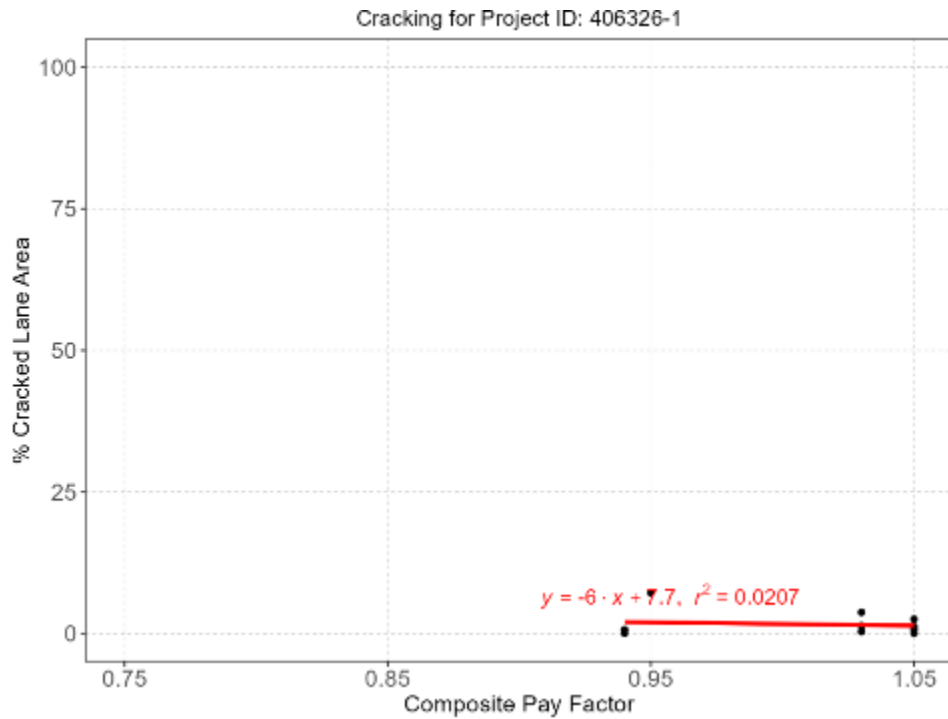


Figure E.12. Total Cracking vs Composite Pay Factor for Project 406326-1

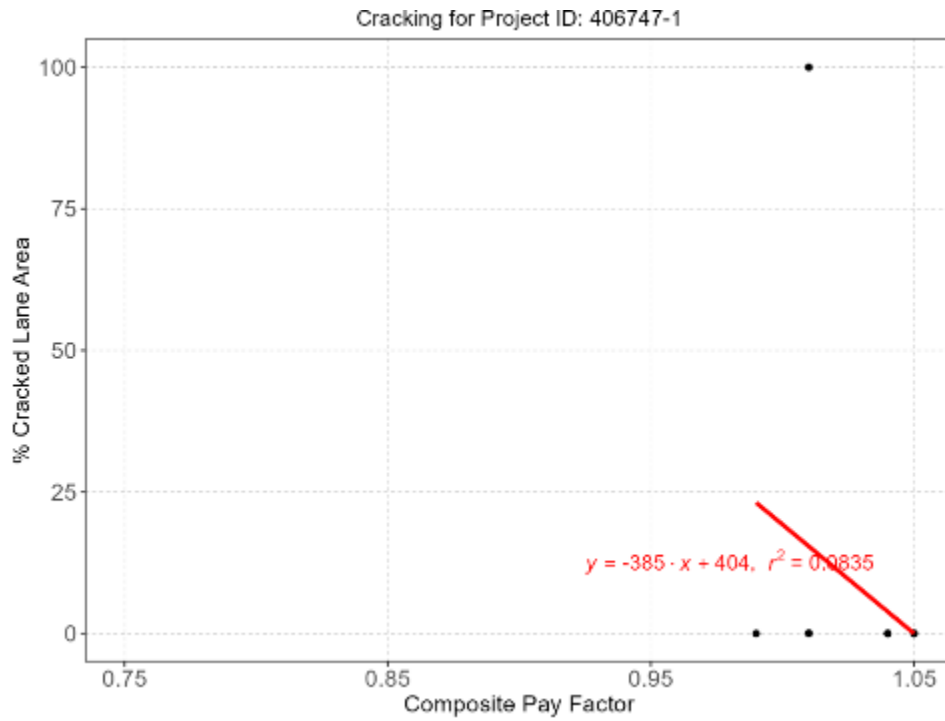


Figure E.13. Total Cracking vs Composite Pay Factor for Project 406747-1

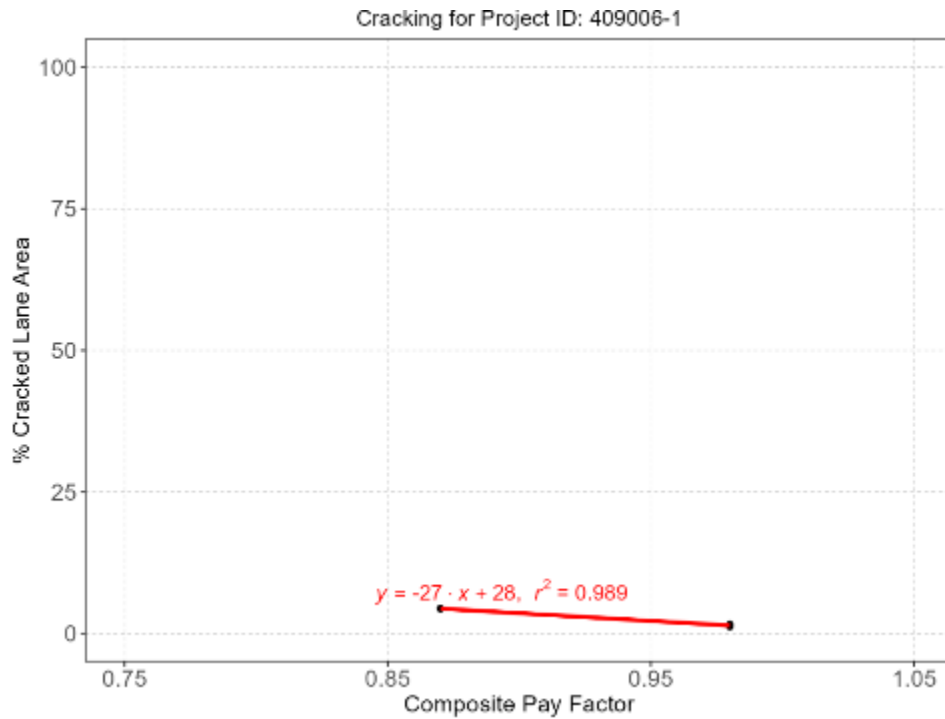


Figure E.14. Total Cracking vs Composite Pay Factor for Project 409006-1

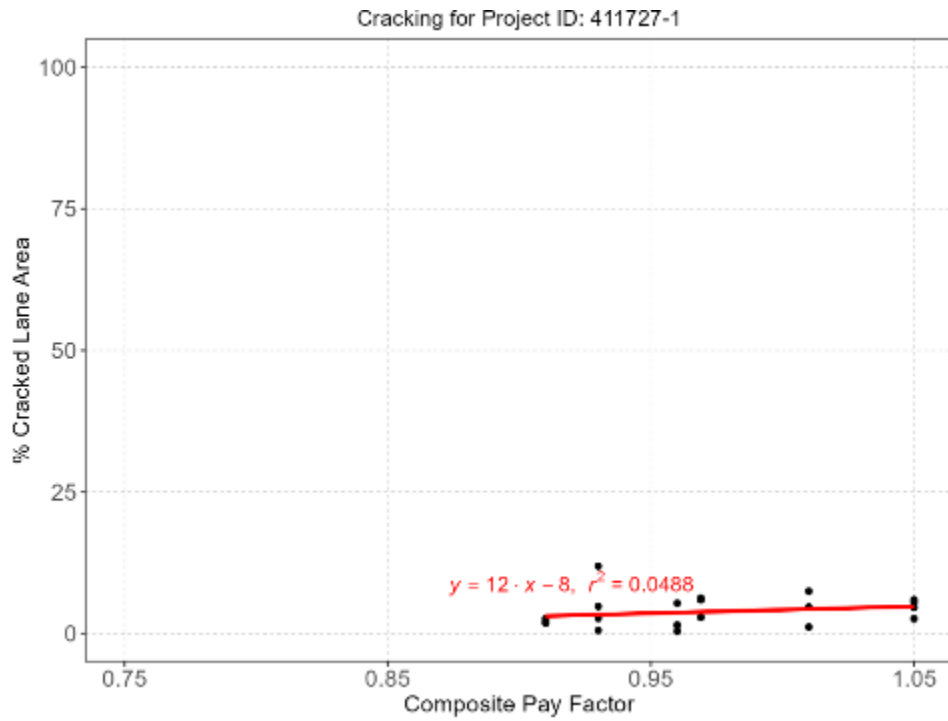


Figure E.15. Total Cracking vs Composite Pay Factor for Project 411727-1

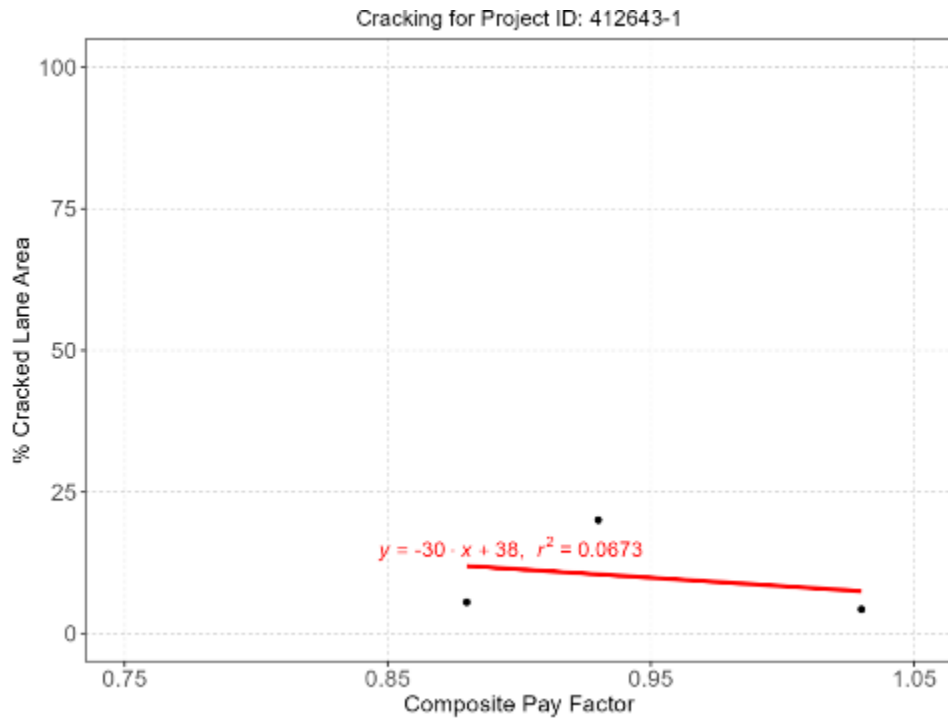


Figure E.16. Total Cracking vs Composite Pay Factor for Project 412643-1

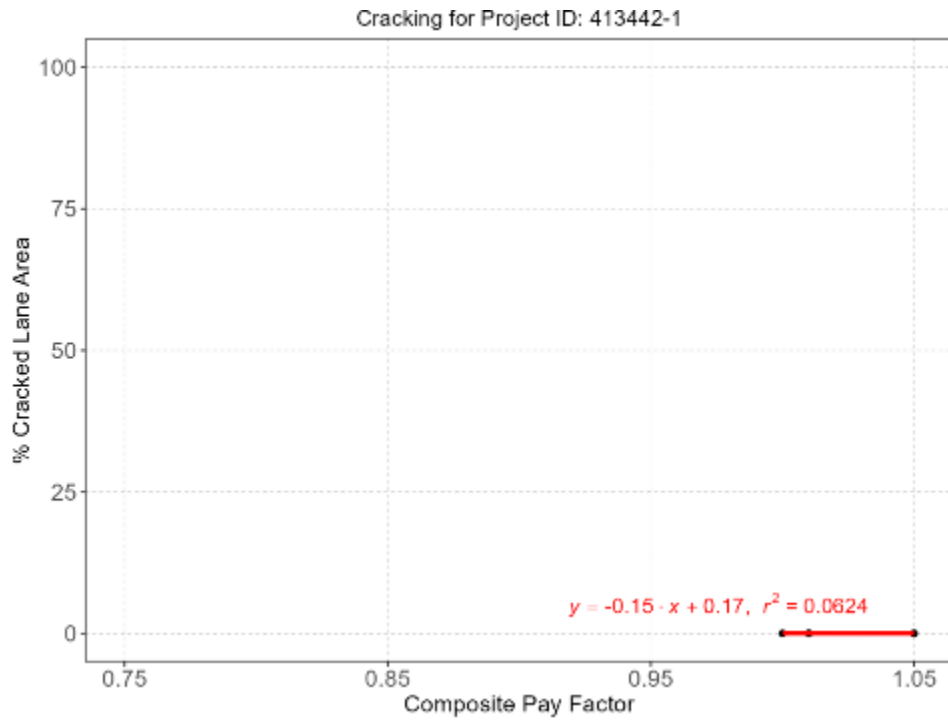


Figure E.17. Total Cracking vs Composite Pay Factor for Project 413442-1

**APPENDIX F: PROJECT LEVEL CORRELATIONS CPF VS
RUTTING FOR OPEN GRADED MIXTURES**

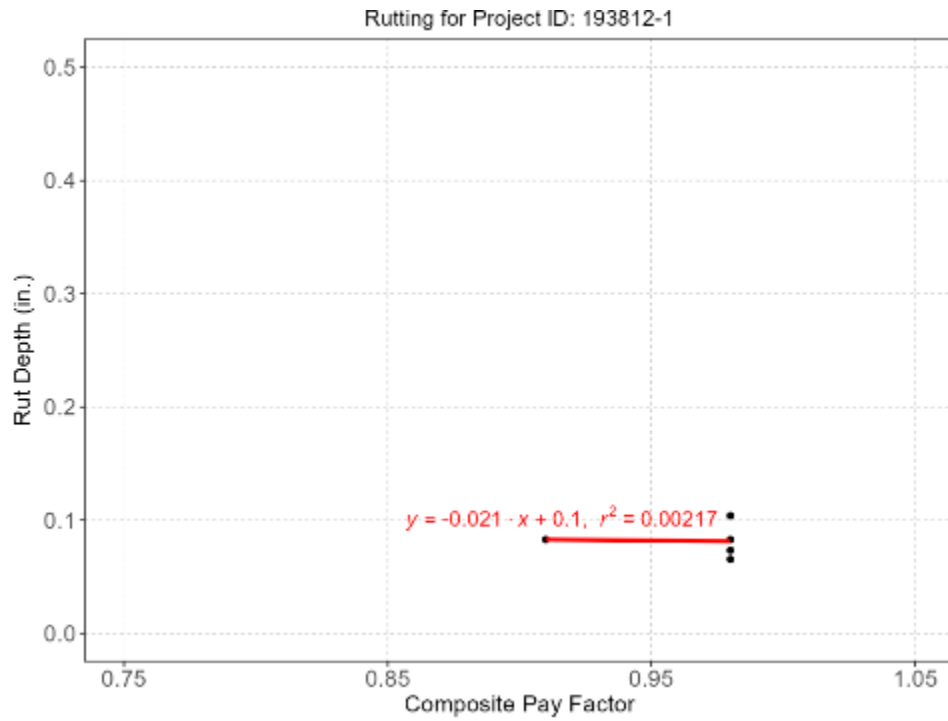


Figure F.1. Rutting vs Composite Pay Factor for Project 193812-1

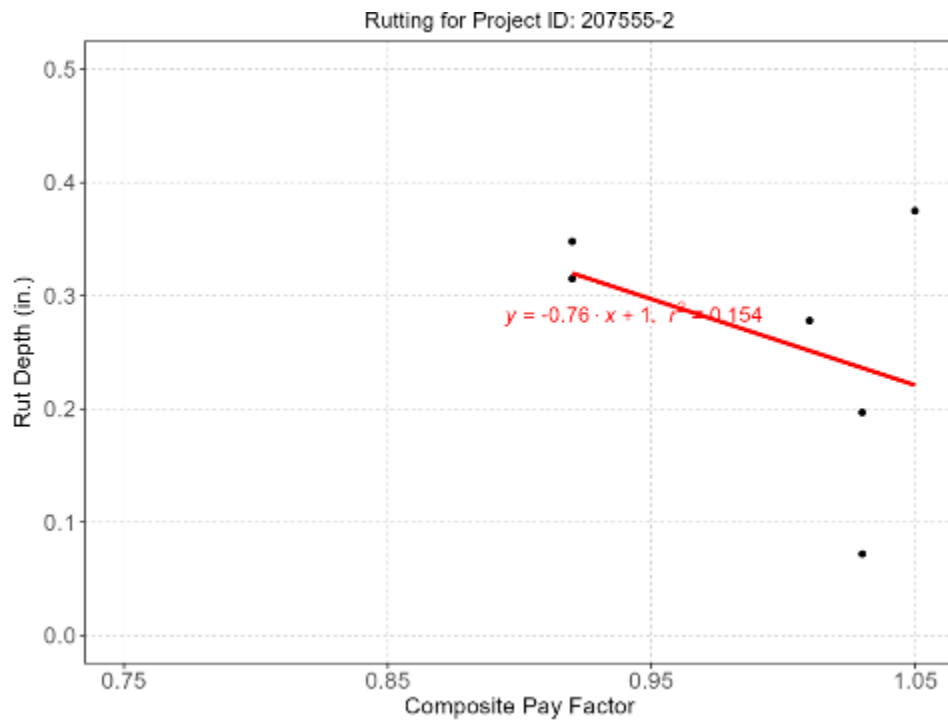


Figure F.2. Rutting vs Composite Pay Factor for Project 207555-2

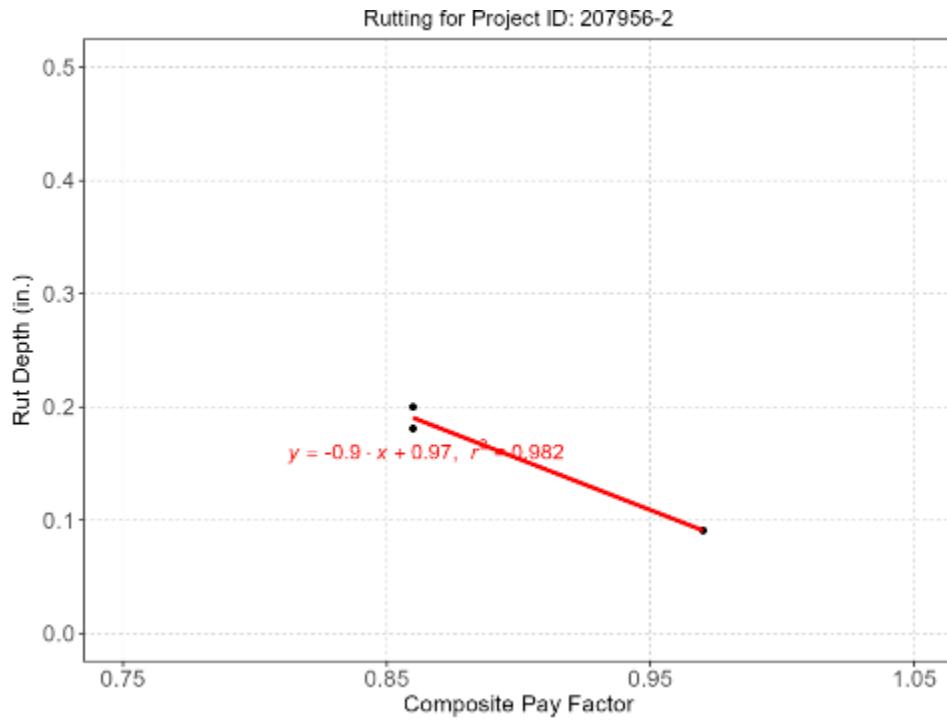


Figure F.3. Rutting vs Composite Pay Factor for Project 207956-2

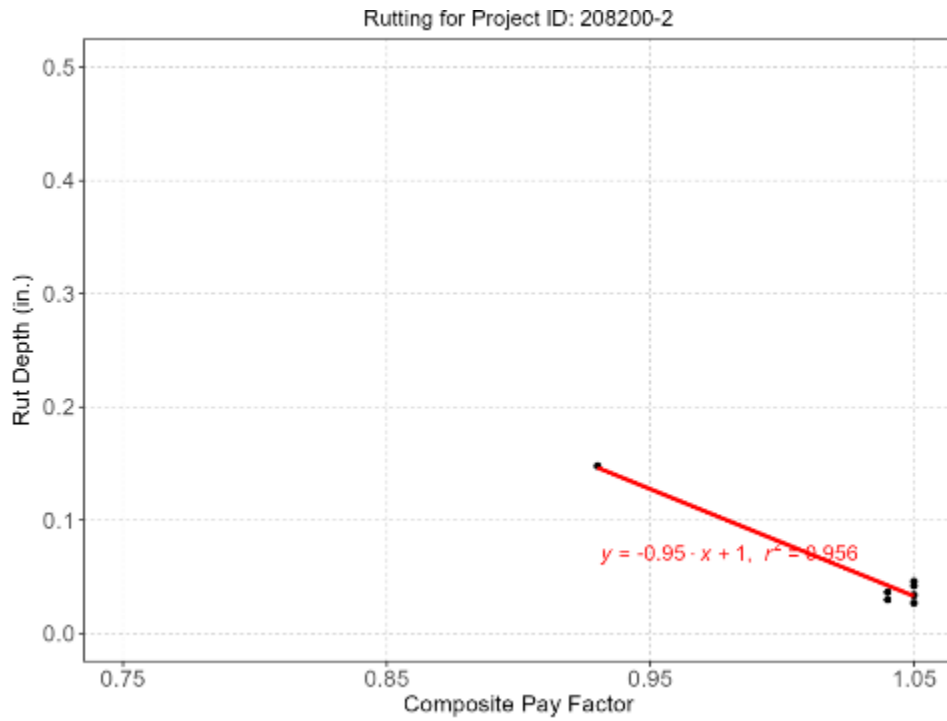


Figure F.4. Rutting vs Composite Pay Factor for Project 208200-2

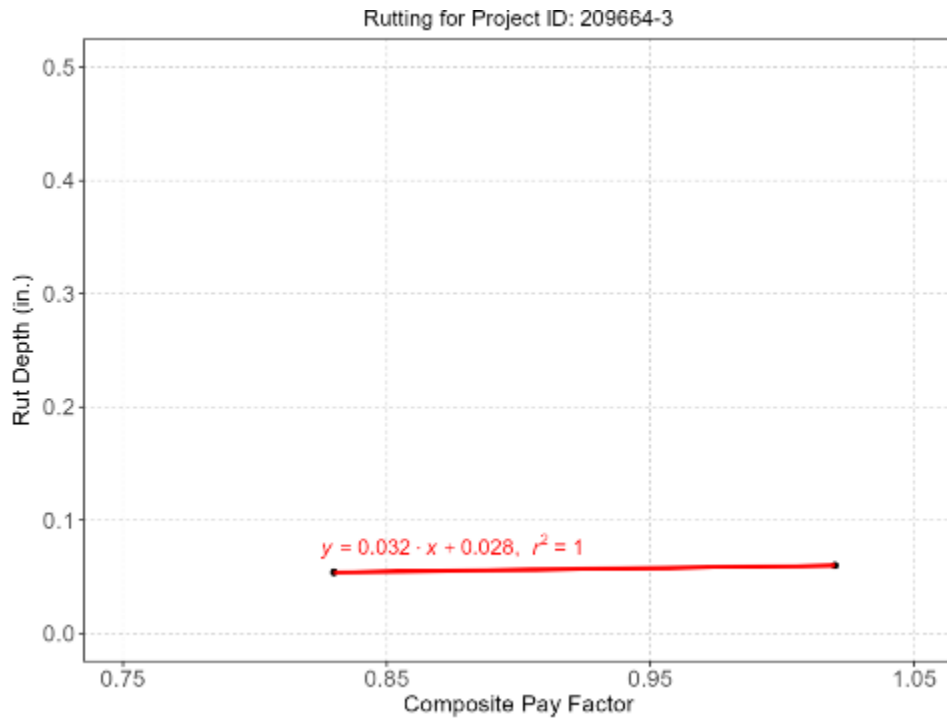


Figure F.5. Rutting vs Composite Pay Factor for Project 209664-3

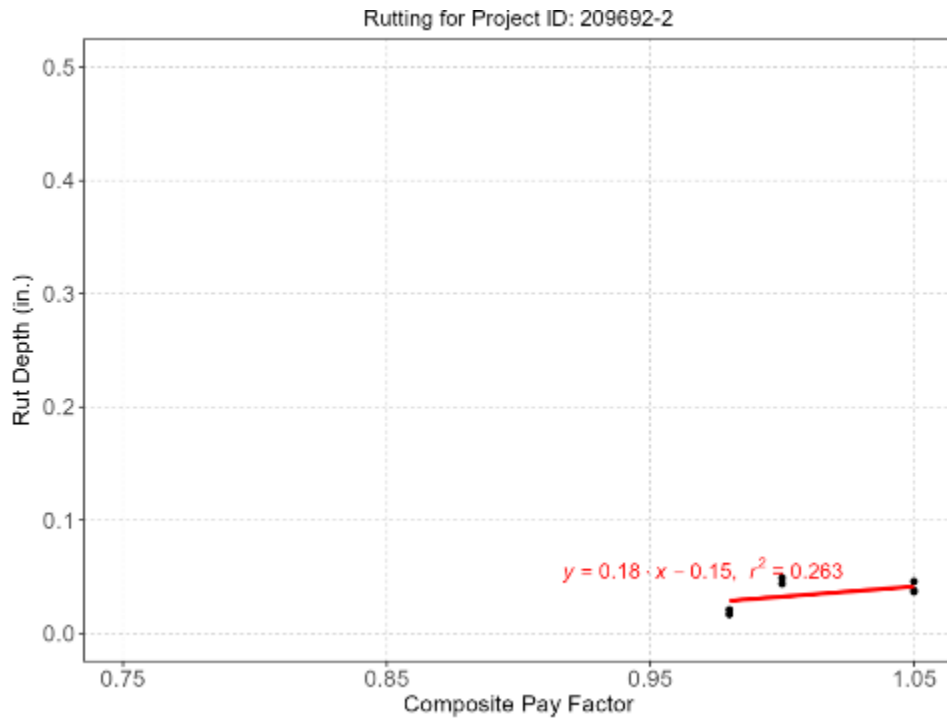


Figure F.6. Rutting vs Composite Pay Factor for Project 209692-2

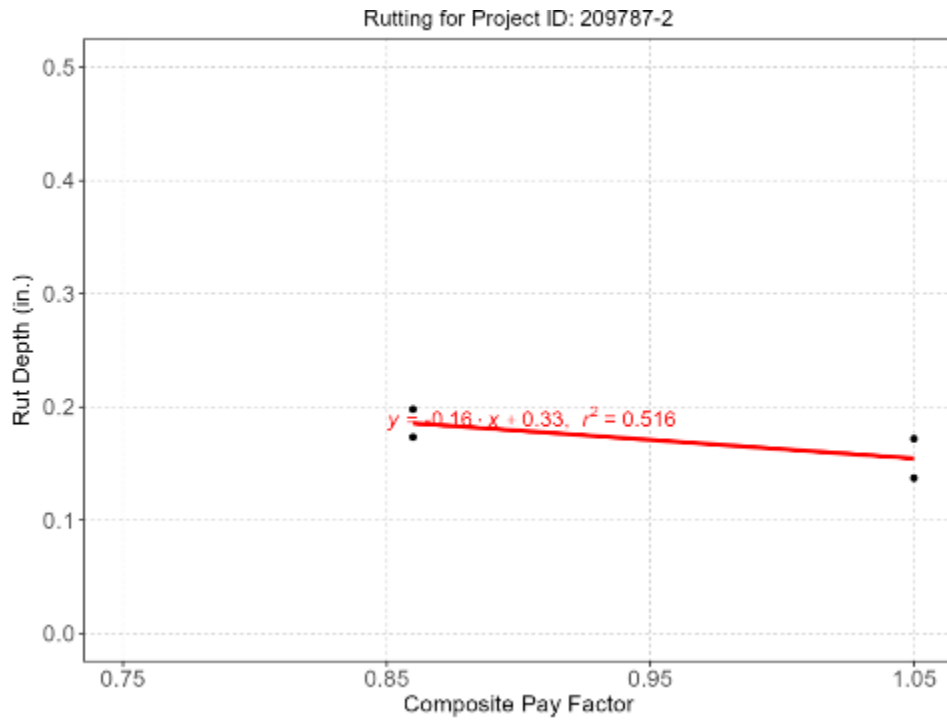


Figure F.7. Rutting vs Composite Pay Factor for Project 209787-2

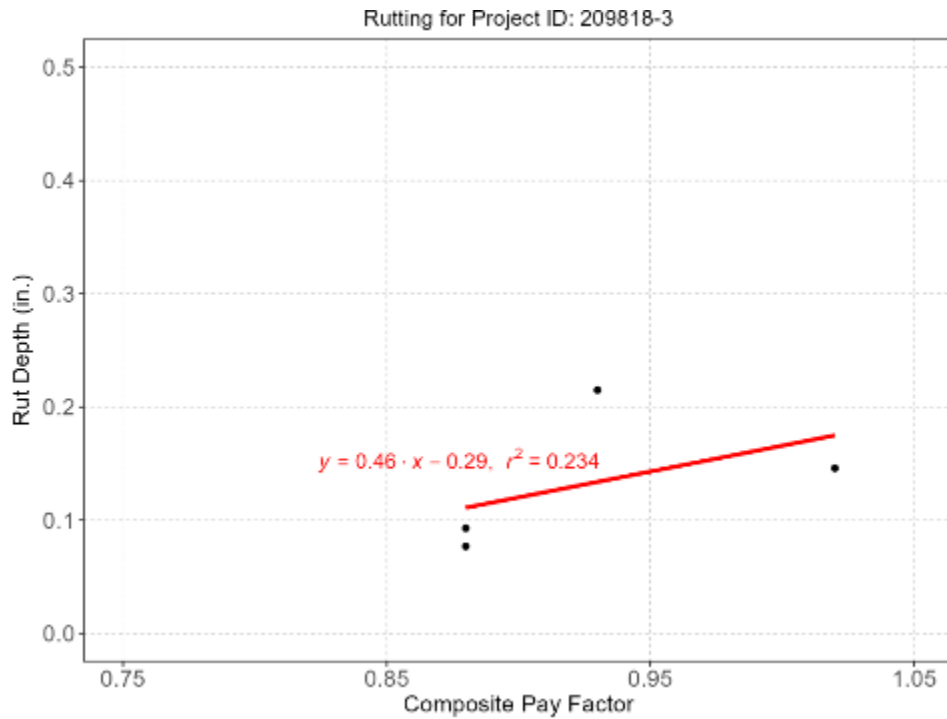


Figure F.8. Rutting vs Composite Pay Factor for Project 209818-3

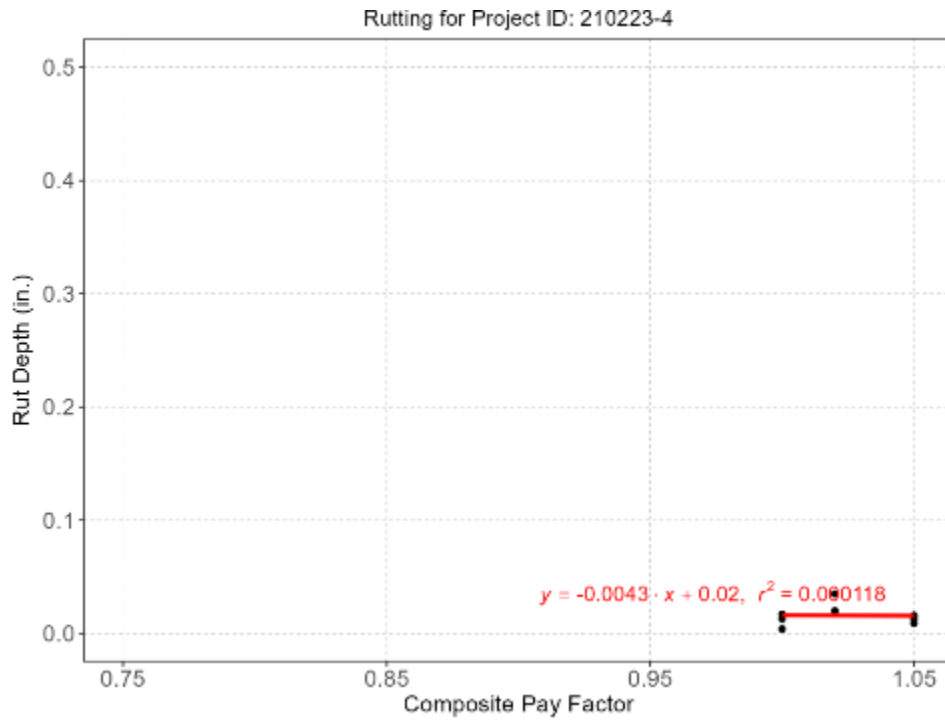


Figure F.9. Rutting vs Composite Pay Factor for Project 210223-4

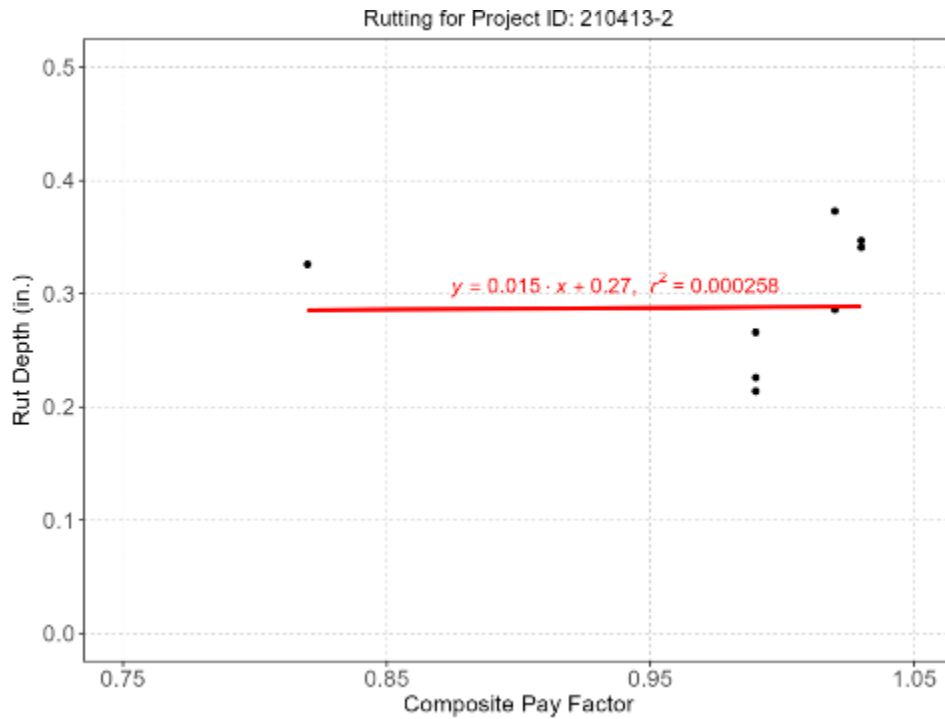


Figure F.10. Rutting vs Composite Pay Factor for Project 210413-2

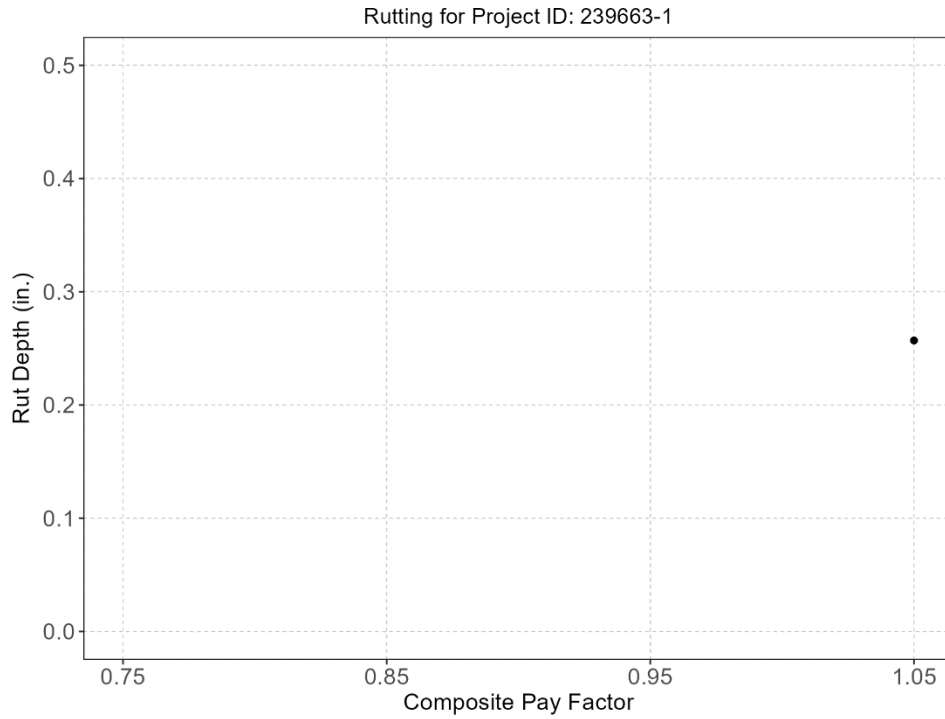


Figure F.11. Rutting vs Composite Pay Factor for Project 239663-1

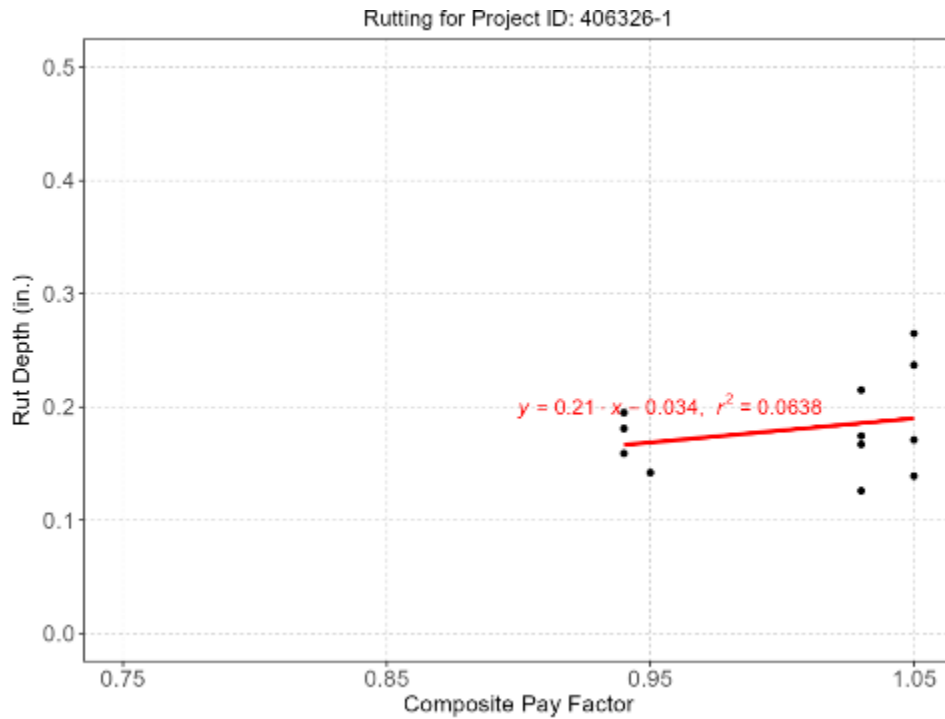


Figure F.12. Rutting vs Composite Pay Factor for Project 406326-1

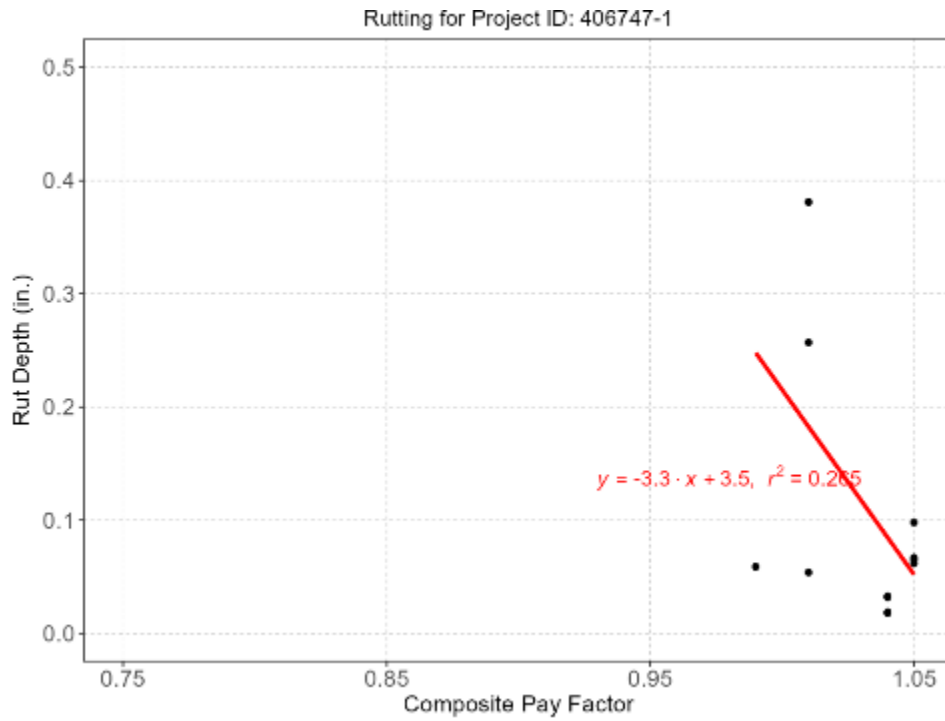


Figure F.13. Rutting vs Composite Pay Factor for Project 406747-1

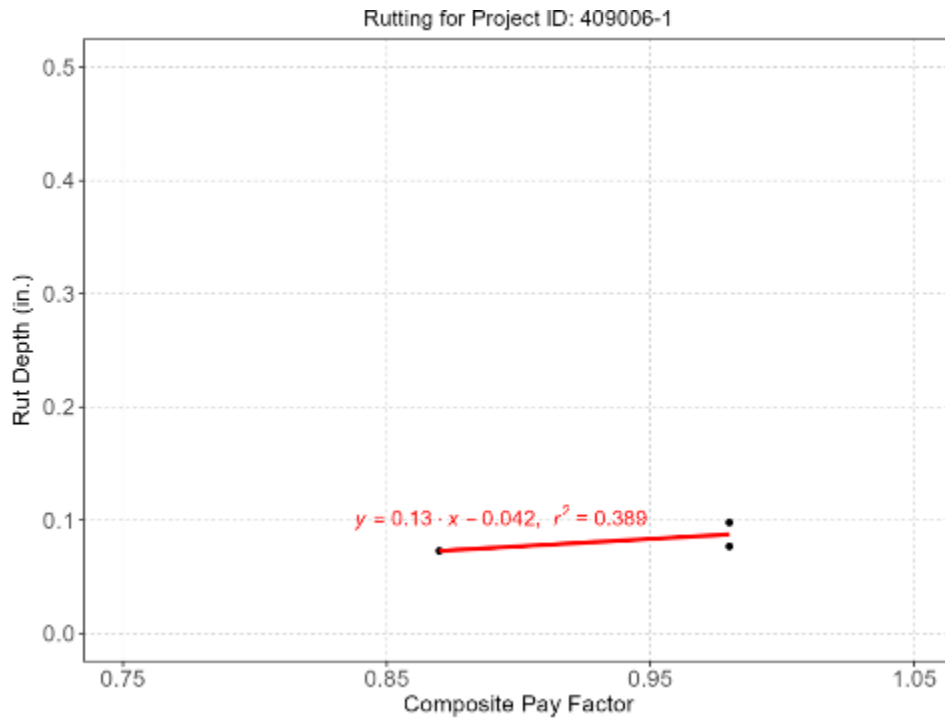


Figure F.14. Rutting vs Composite Pay Factor for Project 409006-1

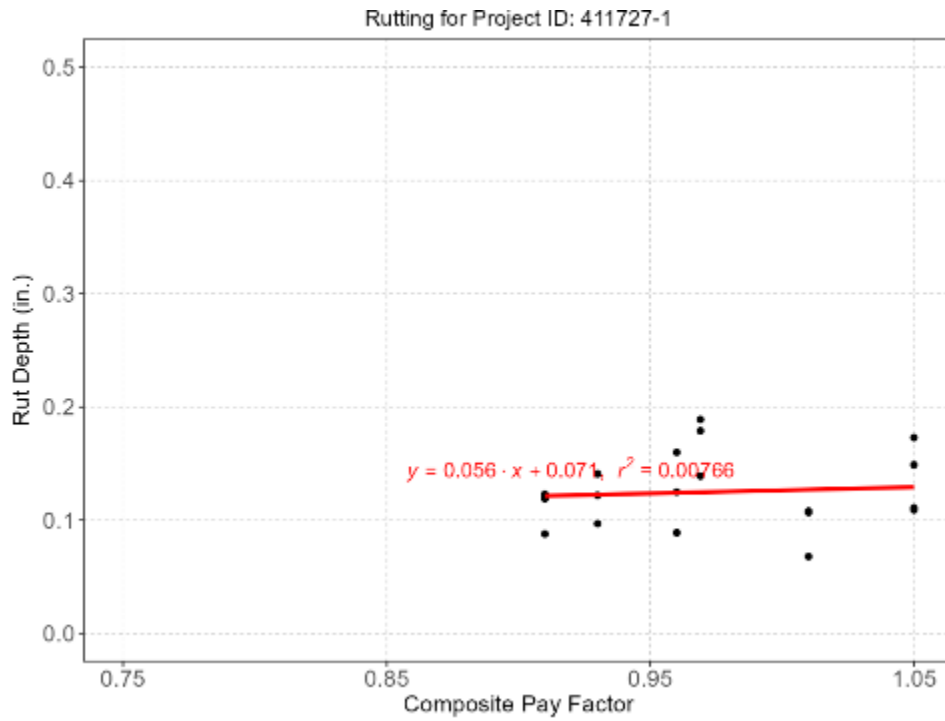


Figure F.15. Rutting vs Composite Pay Factor for Project 411727-1

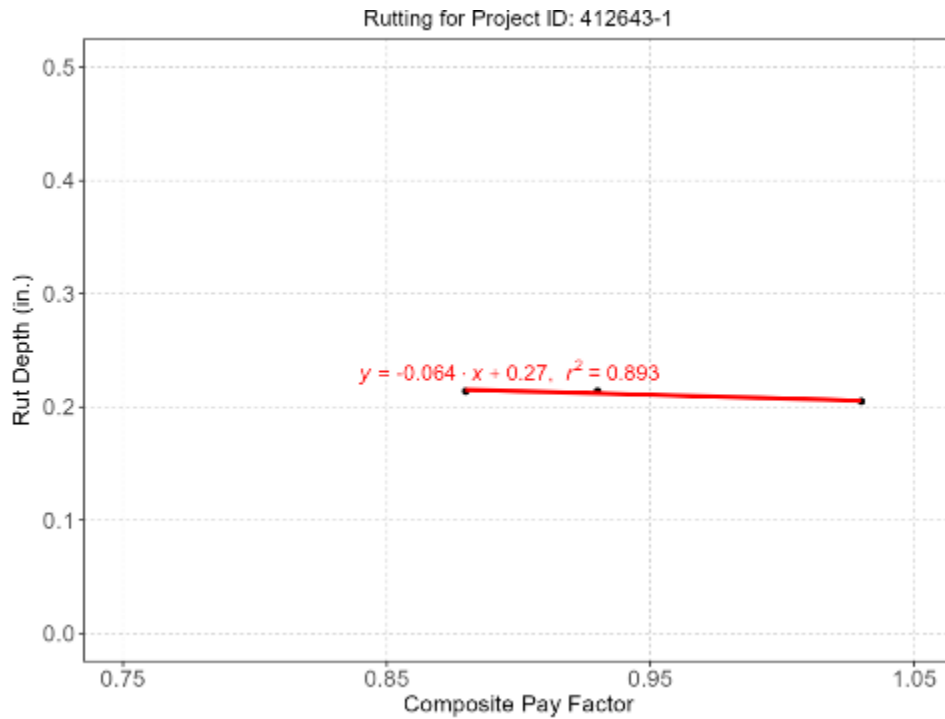


Figure F.16. Rutting vs Composite Pay Factor for Project 412643-1

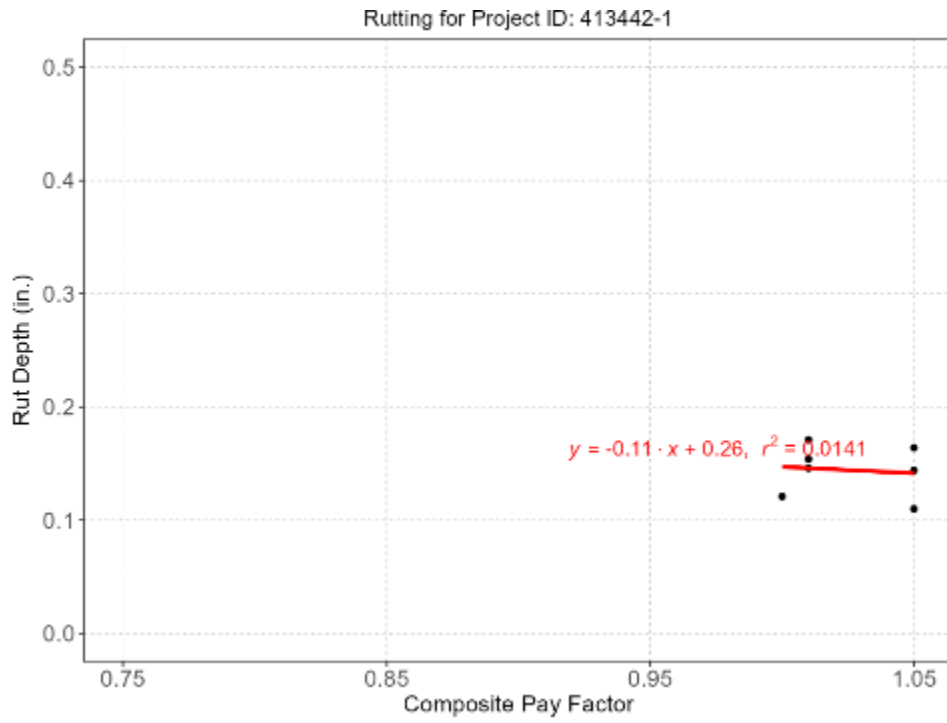


Figure F.17. Rutting vs Composite Pay Factor for Project 413442-1

**APPENDIX G: PROJECT LEVEL CORRELATIONS CPF VS
RAVELING FOR OPEN GRADED MIXTURES**

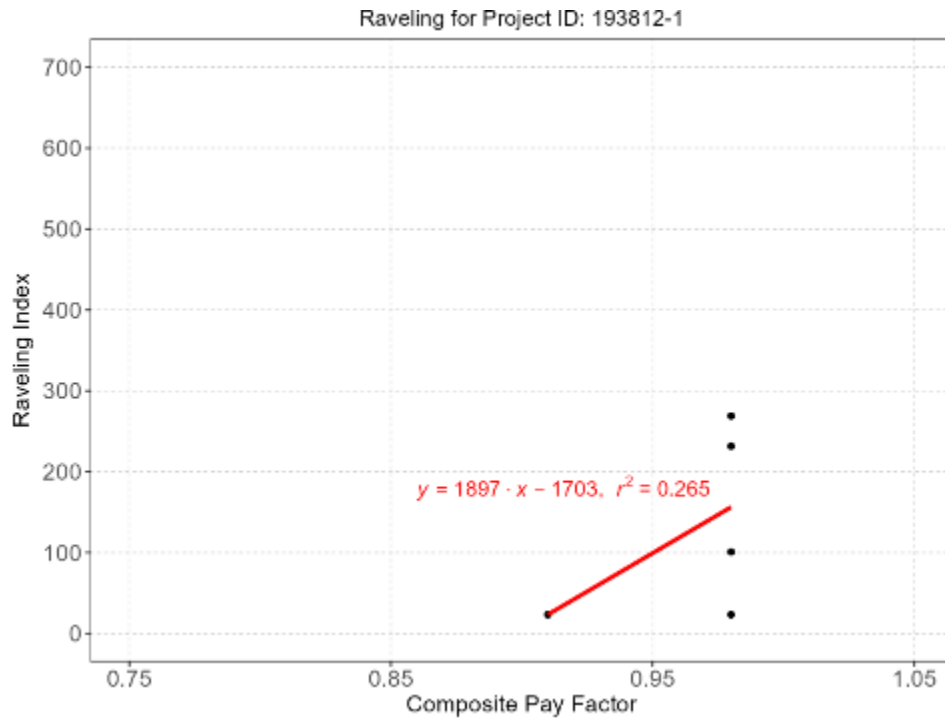


Figure G.1. Raveling vs Composite Pay Factor for Project 193812-1

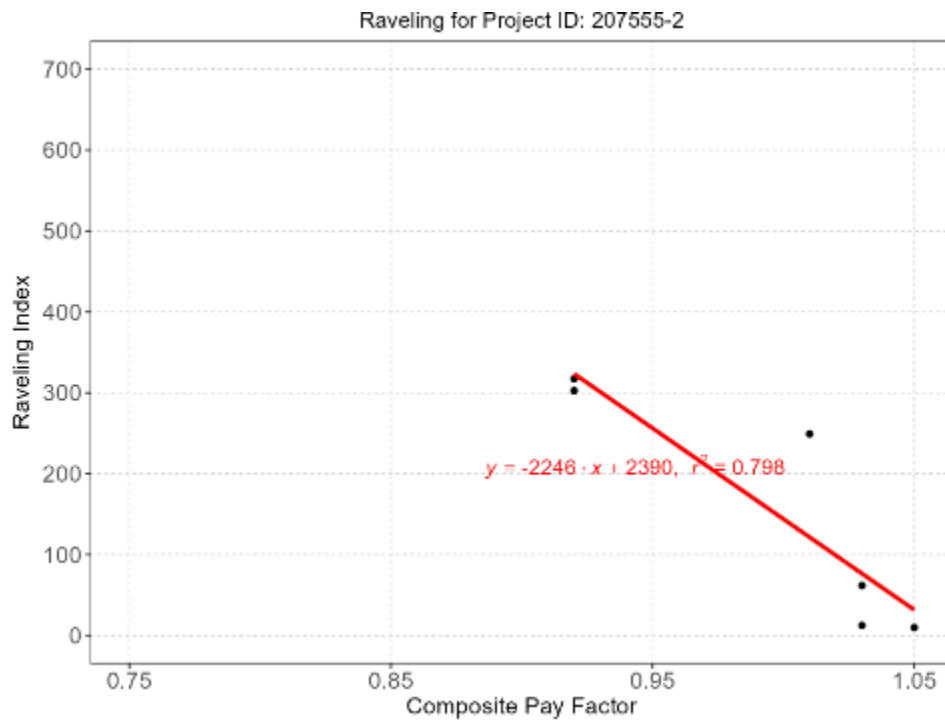


Figure G.2. Raveling vs Composite Pay Factor for Project 207555-2

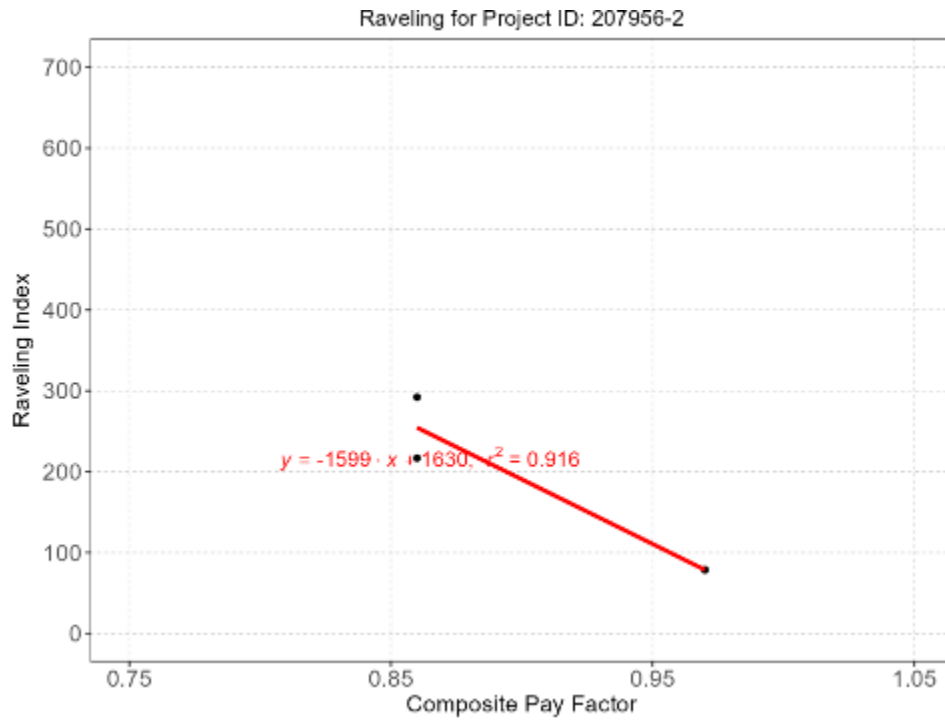


Figure G.3. Raveling vs Composite Pay Factor for Project 207956-2

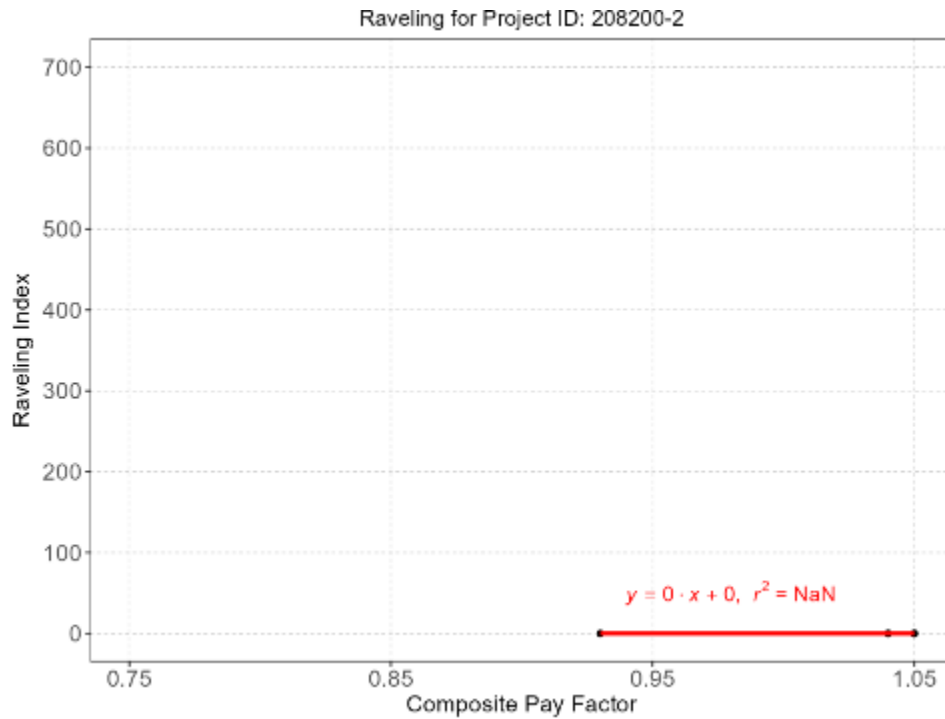


Figure G.4. Raveling vs Composite Pay Factor for Project 208200-2

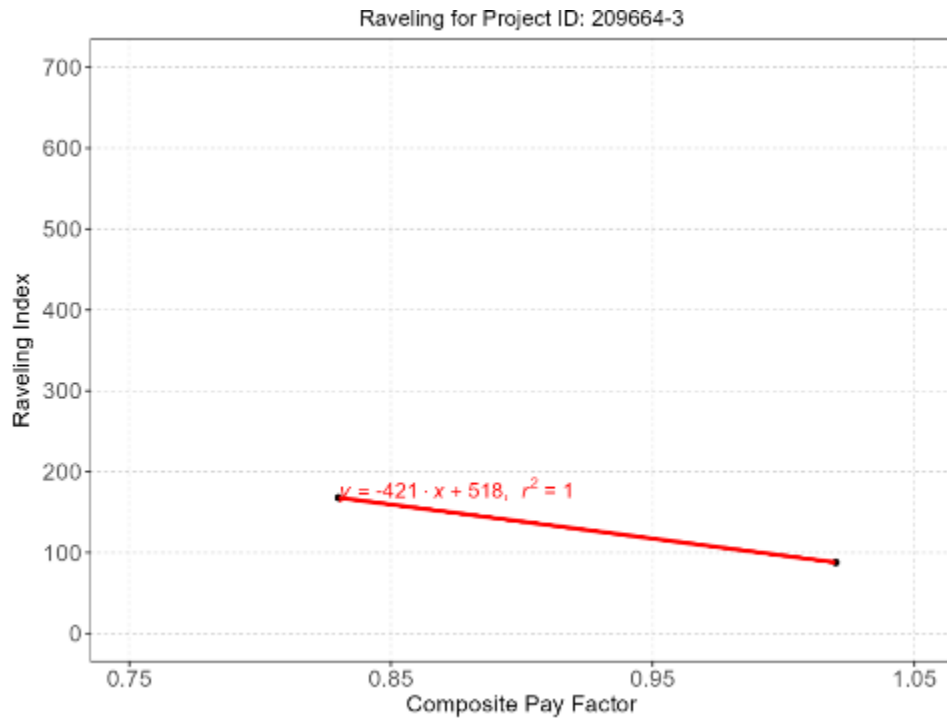


Figure G.5. Raveling vs Composite Pay Factor for Project 209664-3

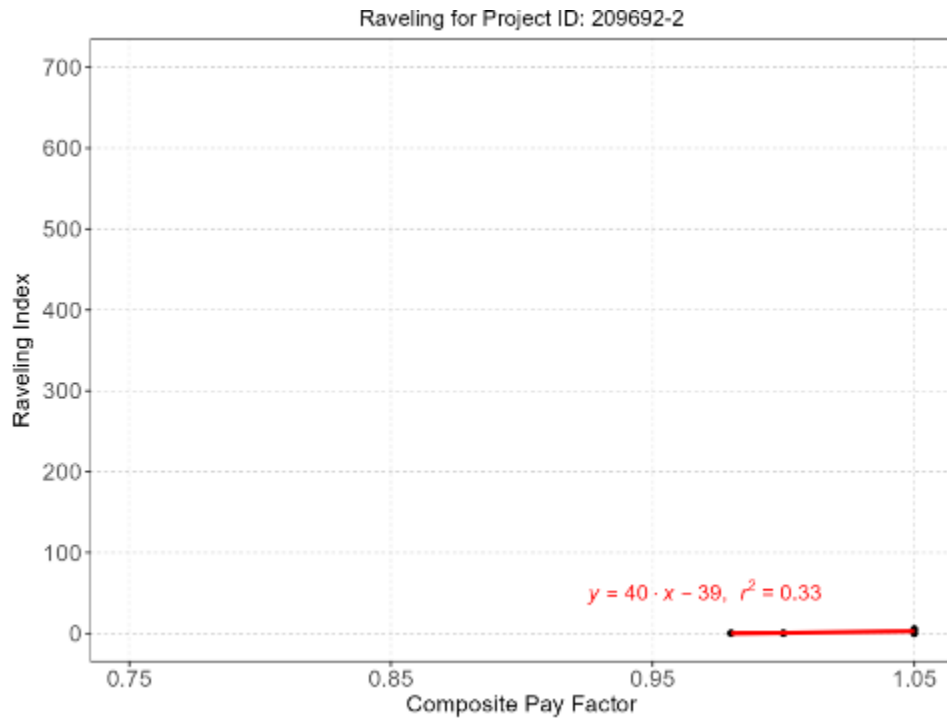


Figure G.6. Raveling vs Composite Pay Factor for Project 209692-2

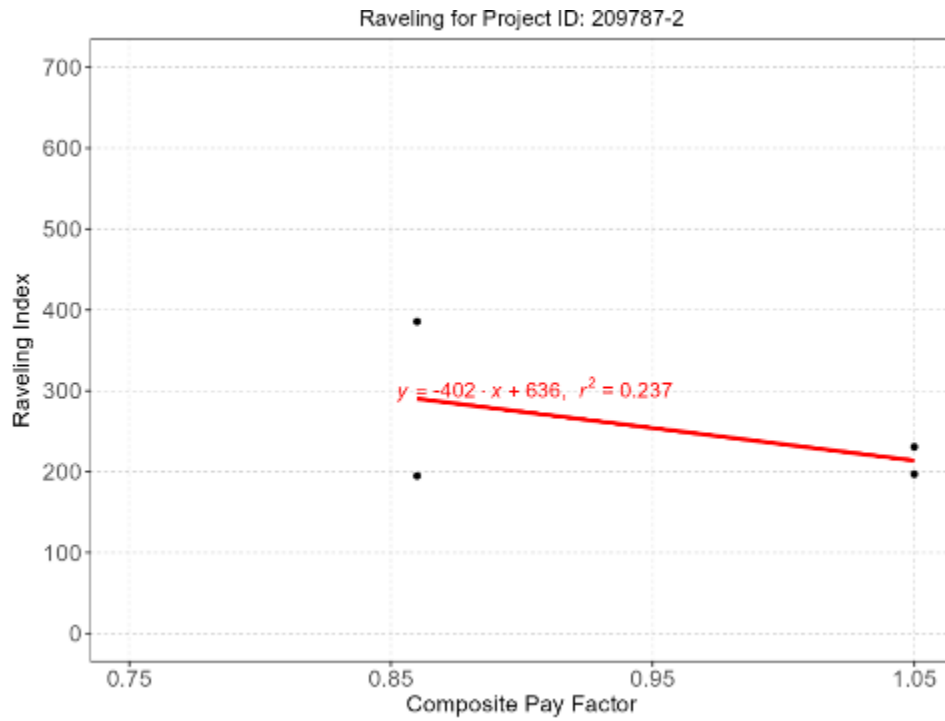


Figure G.7. Raveling vs Composite Pay Factor for Project 209787-2

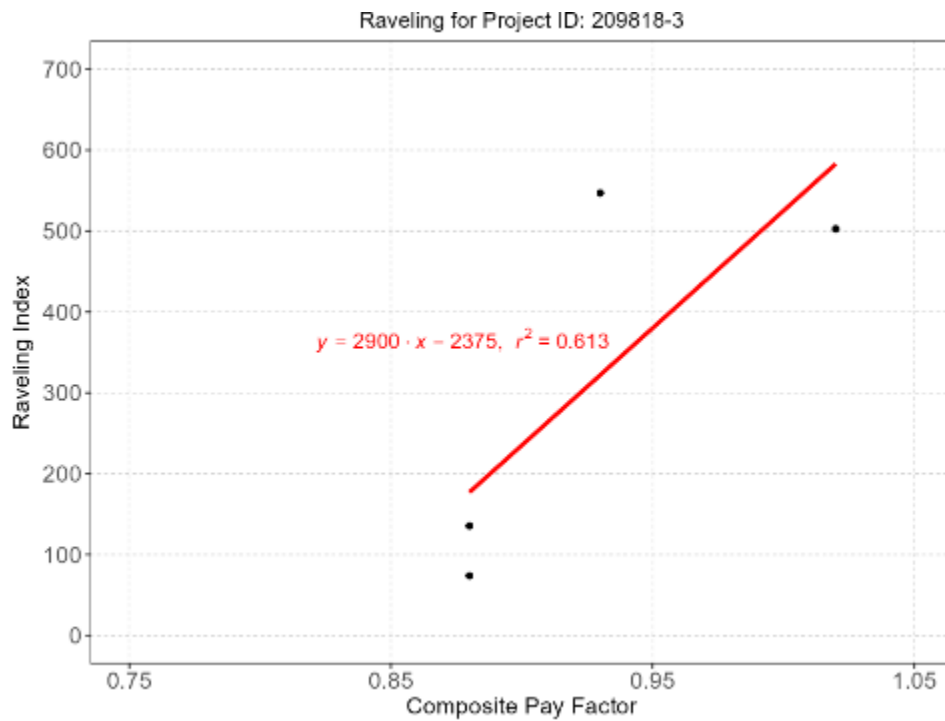


Figure G.8. Raveling vs Composite Pay Factor for Project 209818-3

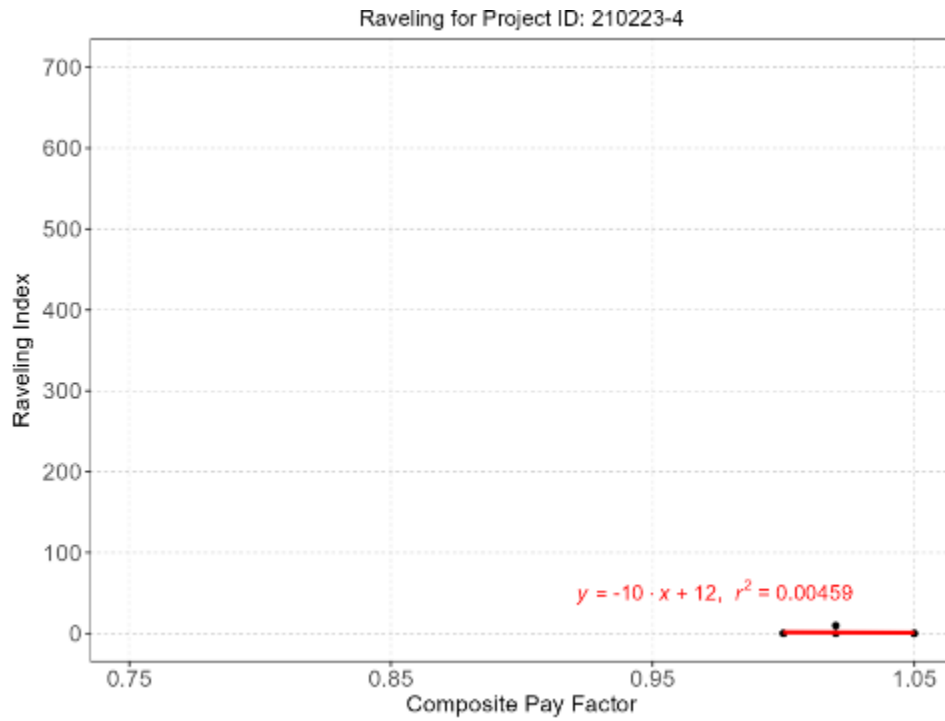


Figure G.9. Raveling vs Composite Pay Factor for Project 210223-4

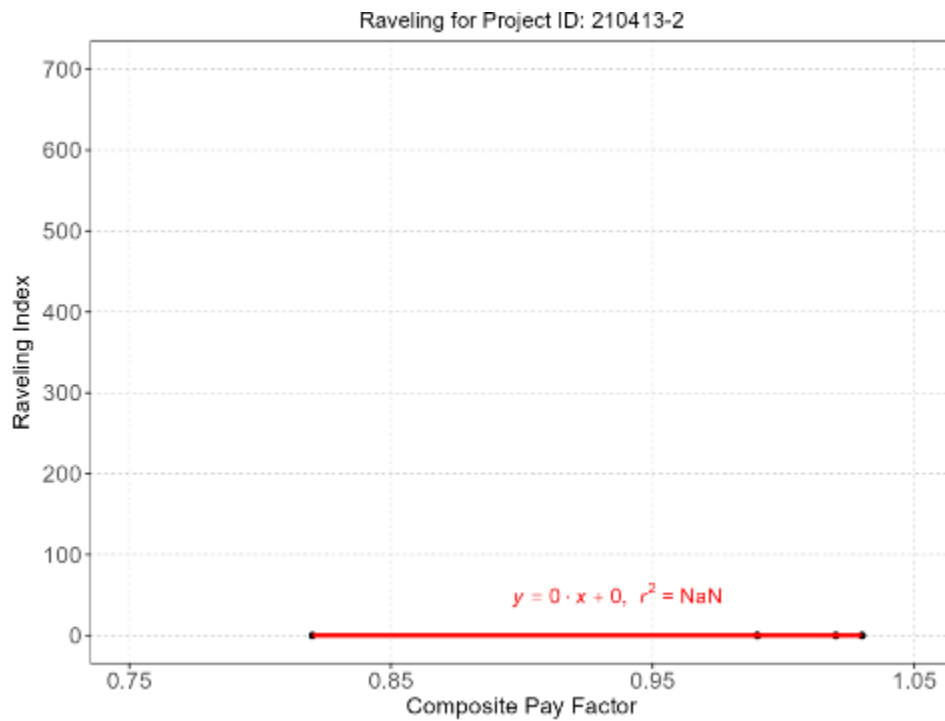


Figure G.10. Raveling vs Composite Pay Factor for Project 210413-2

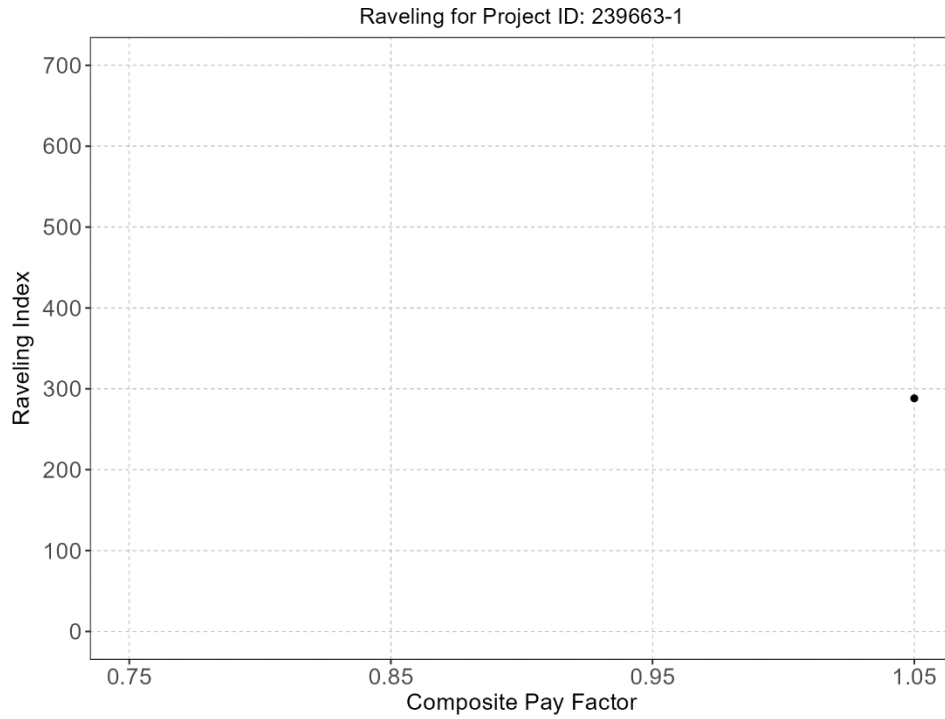


Figure G.11. Raveling vs Composite Pay Factor for Project 239663-1

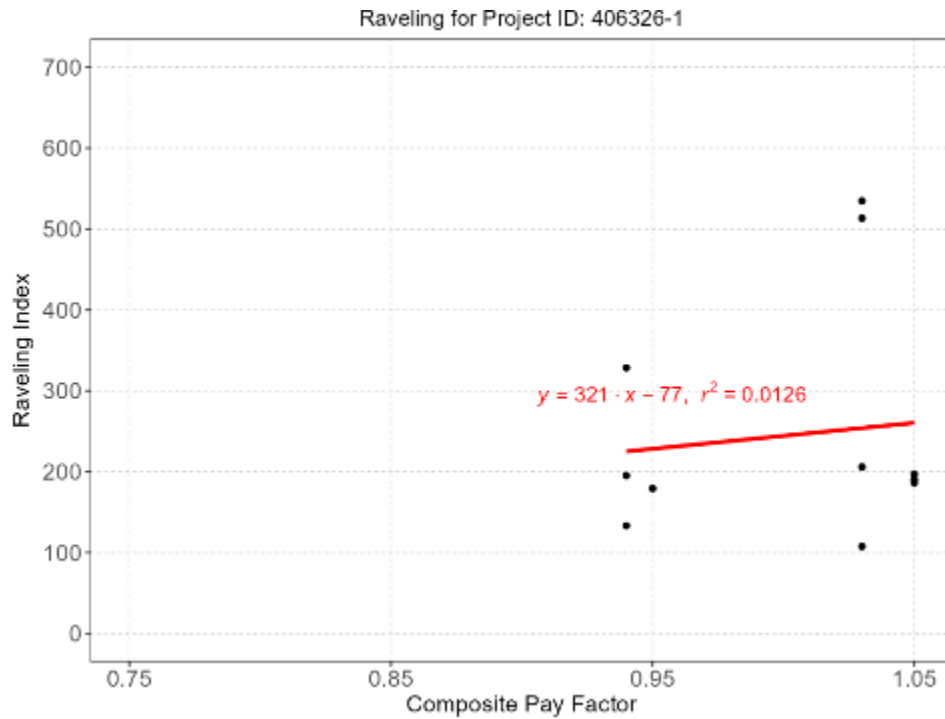


Figure G.12. Raveling vs Composite Pay Factor for Project 406326-1

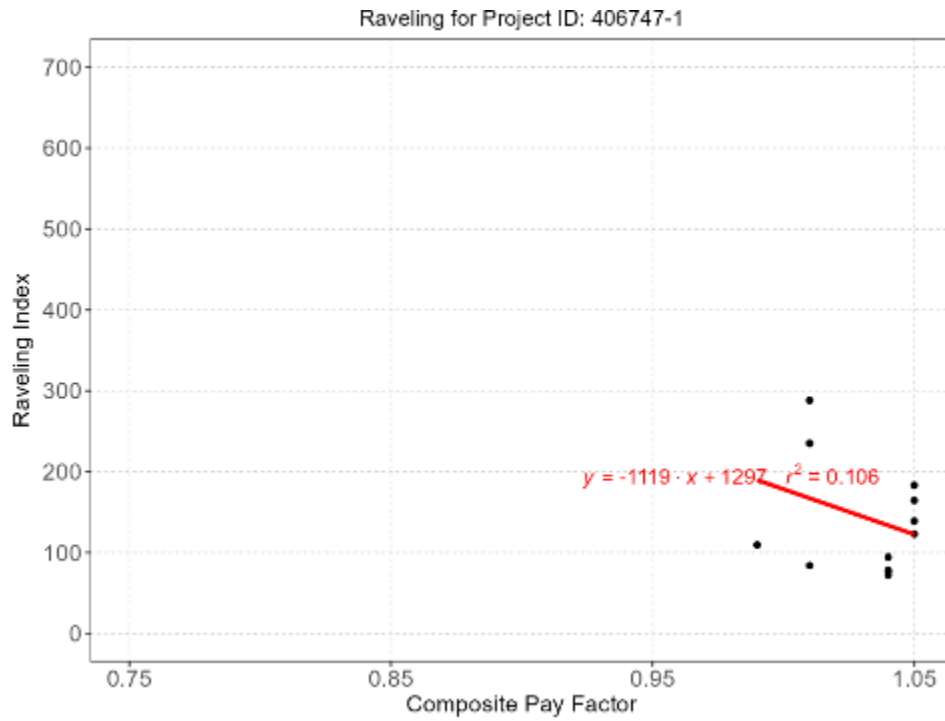


Figure G.13. Raveling vs Composite Pay Factor for Project 406747-1

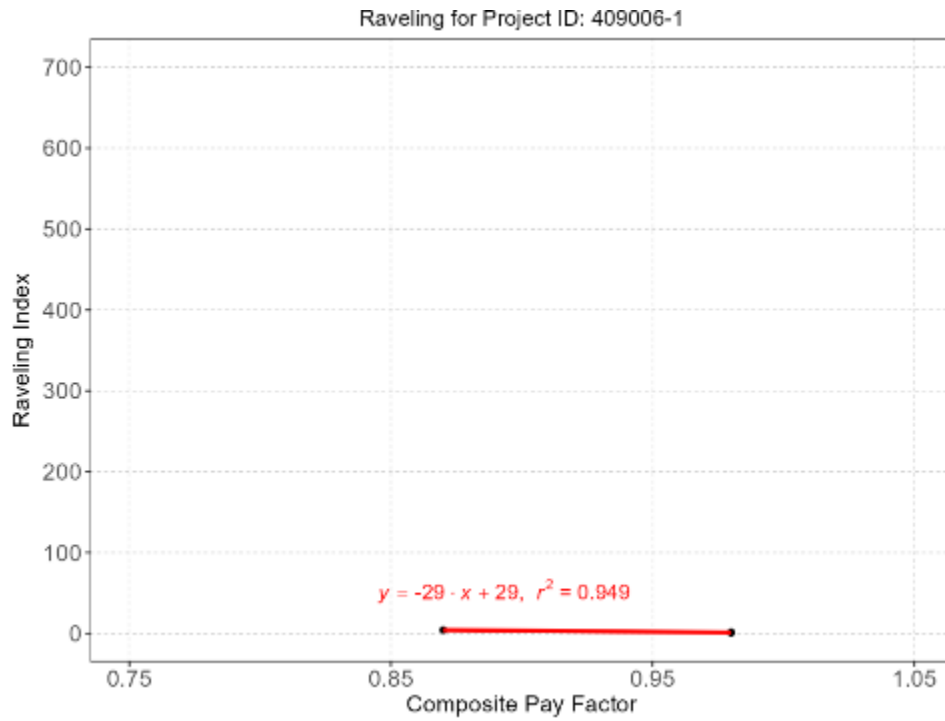


Figure G.14. Raveling vs Composite Pay Factor for Project 409006-1

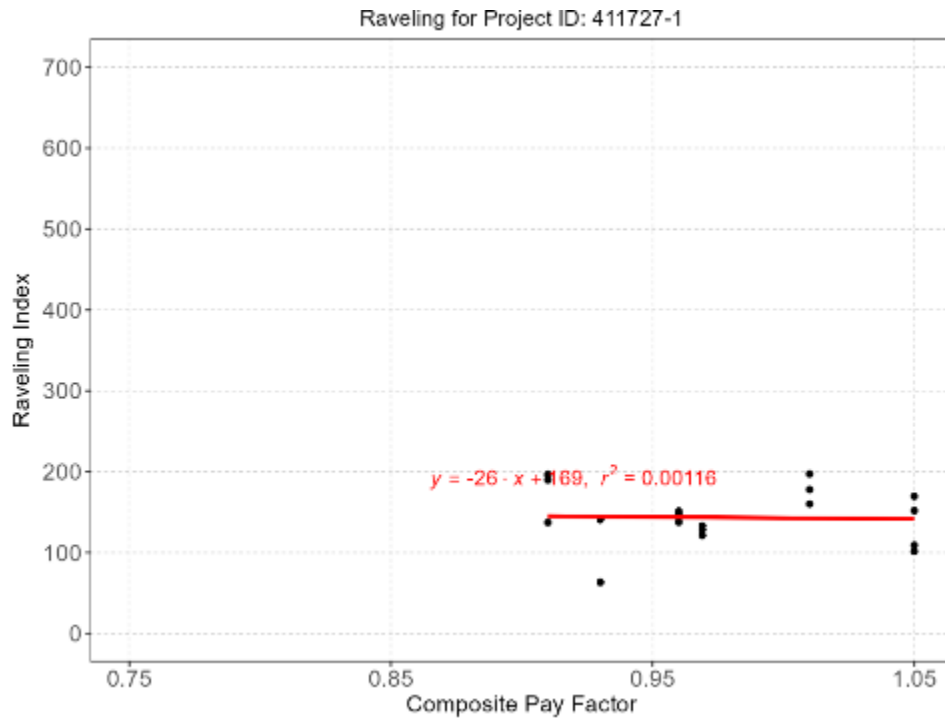


Figure G.15. Raveling vs Composite Pay Factor for Project 411727-1

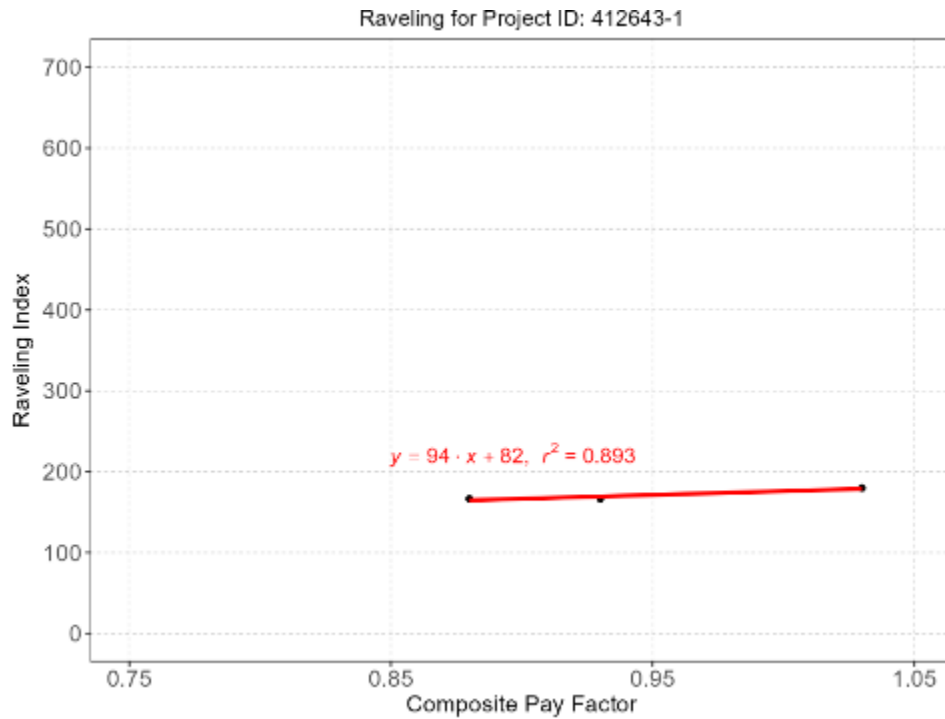


Figure G.16. Raveling vs Composite Pay Factor for Project 412643-1

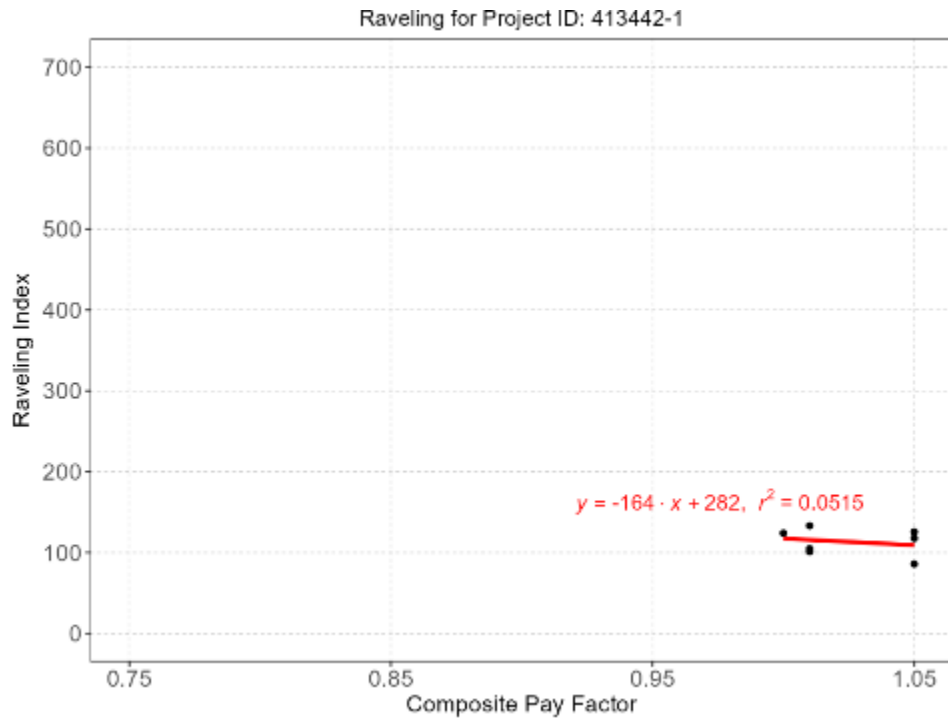


Figure G.17. Raveling vs Composite Pay Factor for Project 413442-1

**APPENDIX H: MULTINOMIAL LOGISTIC ANALYSIS
FIGURES FOR CRACKING OF DENSE GRADED MIXTURES**

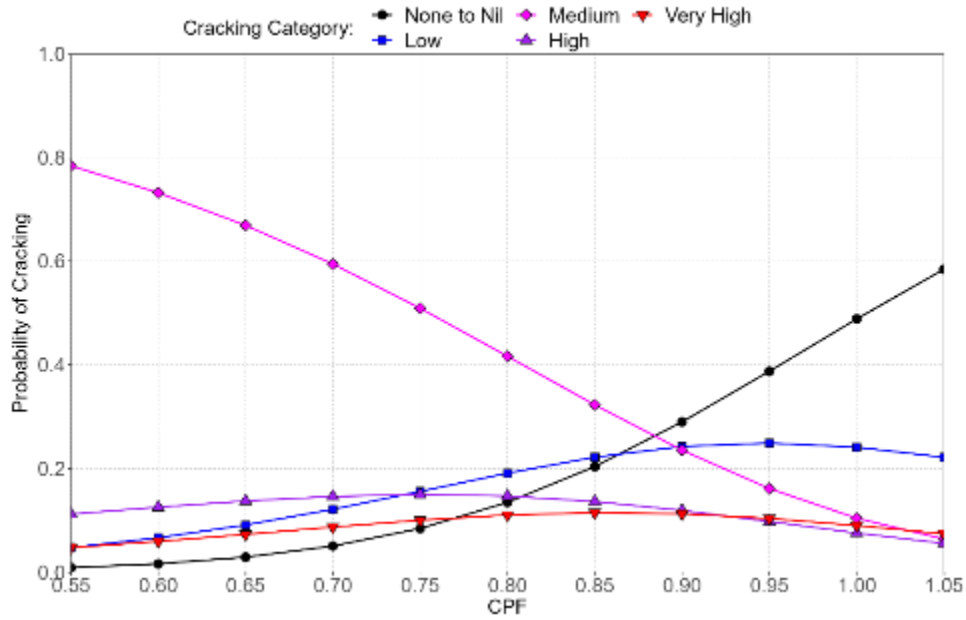


Figure H.1. Logistic Regression Predicted Probability of Cracking vs. CPF (Dense Graded)

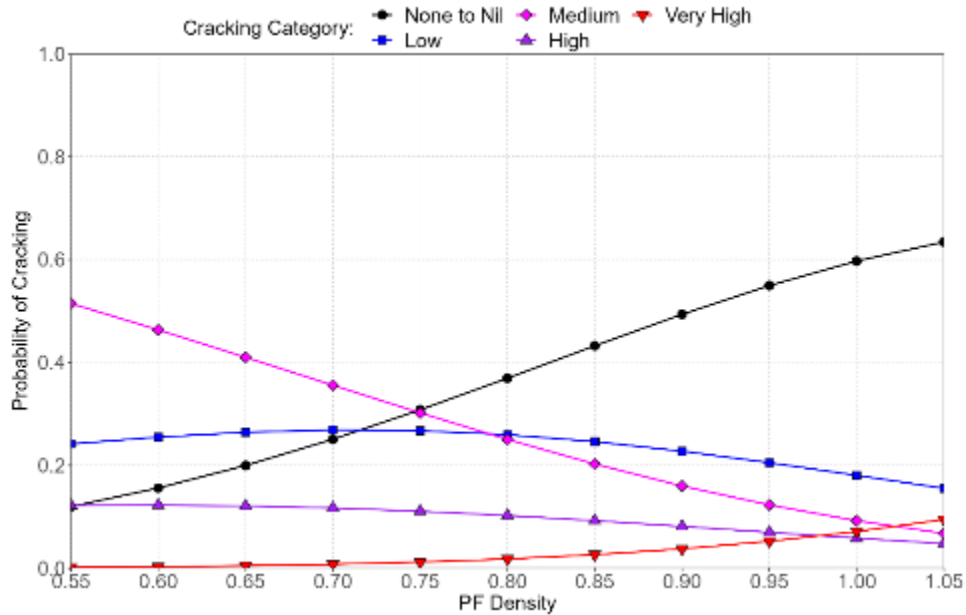


Figure H.2. Logistic Regression Predicted Probability of Cracking vs. Density PF (Dense Graded)

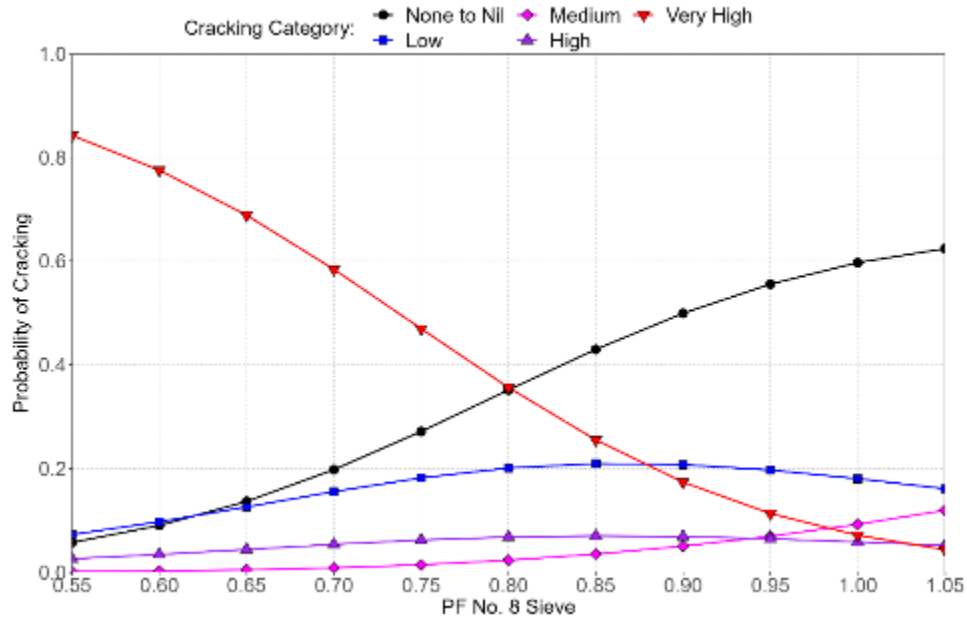


Figure H.3. Logistic Regression Predicted Probability of Cracking vs. P8 PF (Dense Graded)

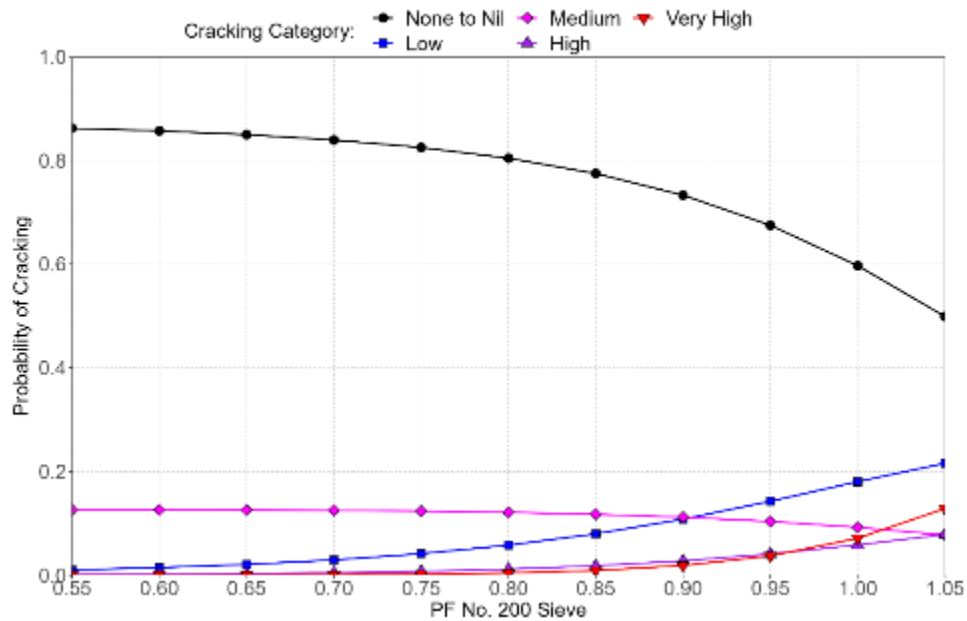


Figure H.4. Logistic Regression Predicted Probability of Cracking vs. P200 PF (Dense Graded)

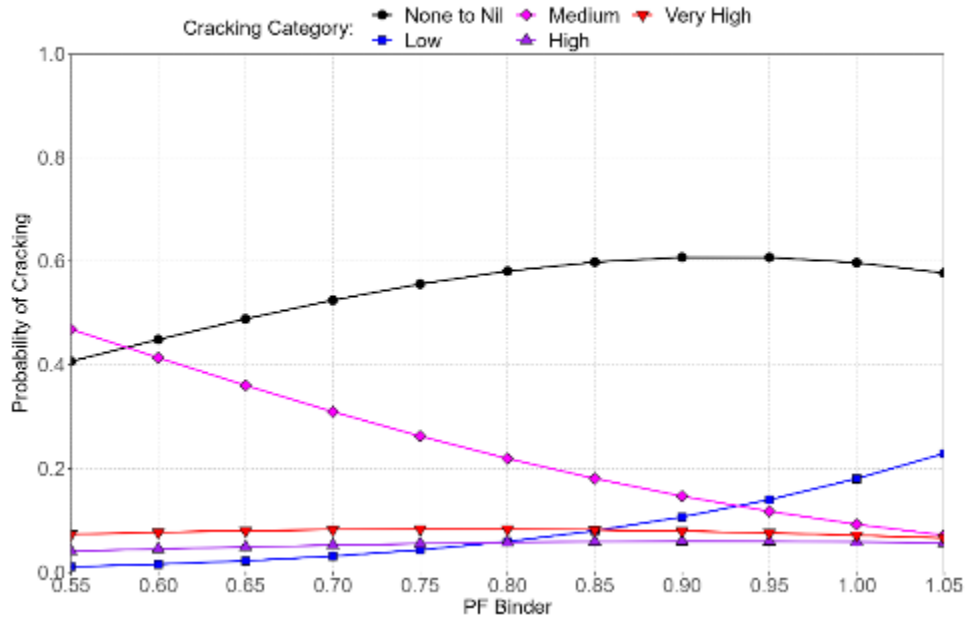


Figure H.5. Logistic Regression Predicted Probability of Cracking vs. Pb PF (Dense Graded)

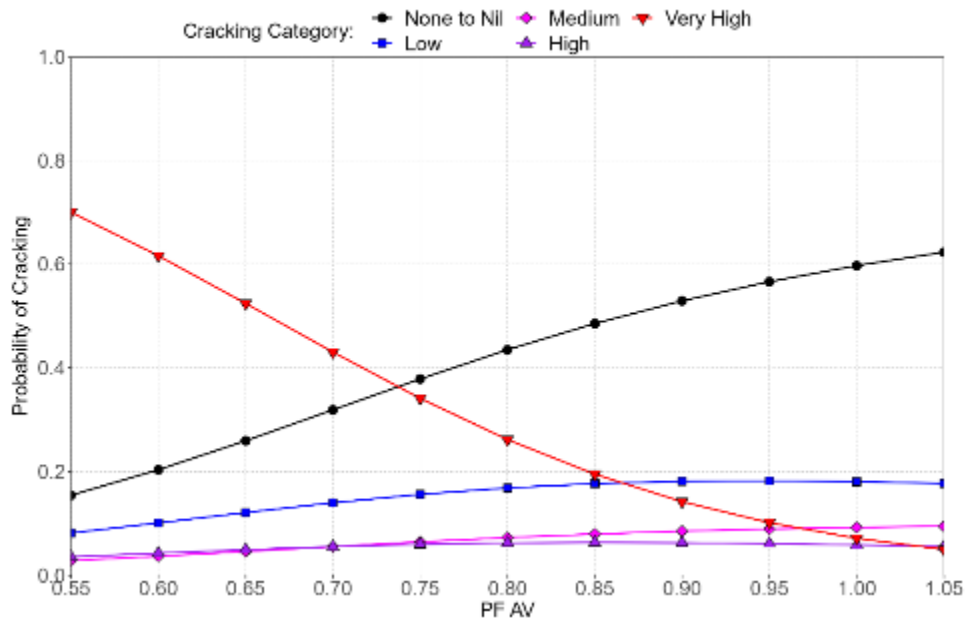


Figure H.6. Logistic Regression Predicted Probability of Cracking vs. Va PF (Dense Graded)

**APPENDIX I: MULTINOMIAL LOGISTIC ANALYSIS FIGURES
FOR CRACKING OF OPEN GRADED MIXTURES**

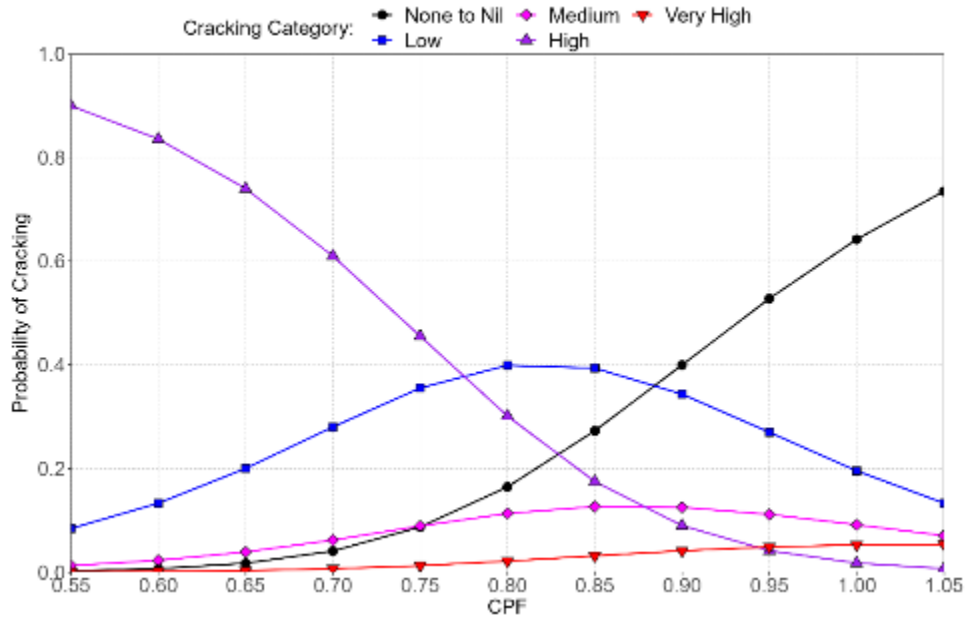


Figure I.1. Logistic Regression Predicted Probability of Cracking vs. CPF (Open Graded)

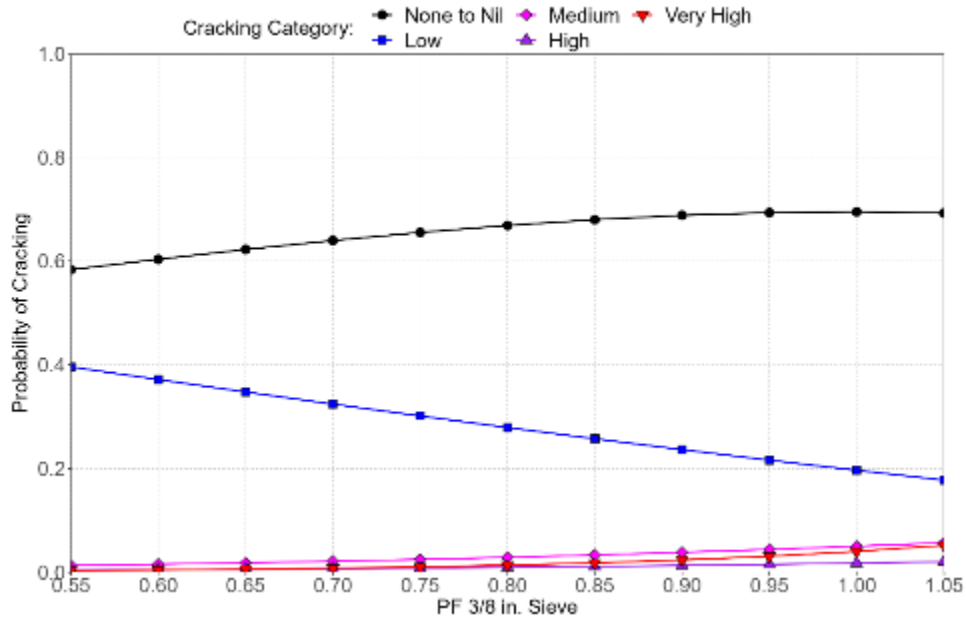


Figure I.2. Logistic Regression Predicted Probability of Cracking vs. P3.8 PF (Open Graded)

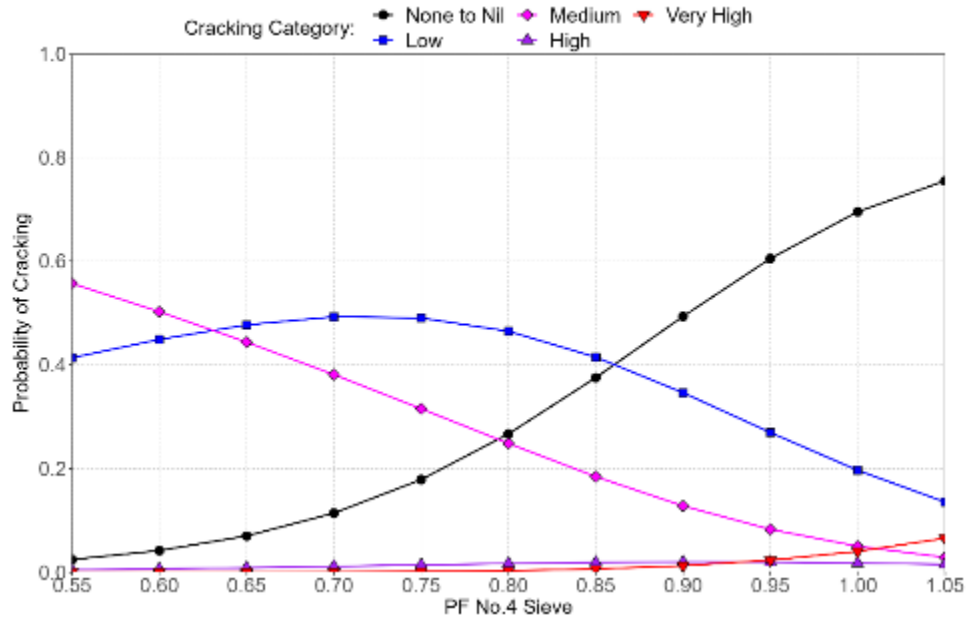


Figure I.3. Logistic Regression Predicted Probability of Cracking vs. P4 PF (Open Graded)

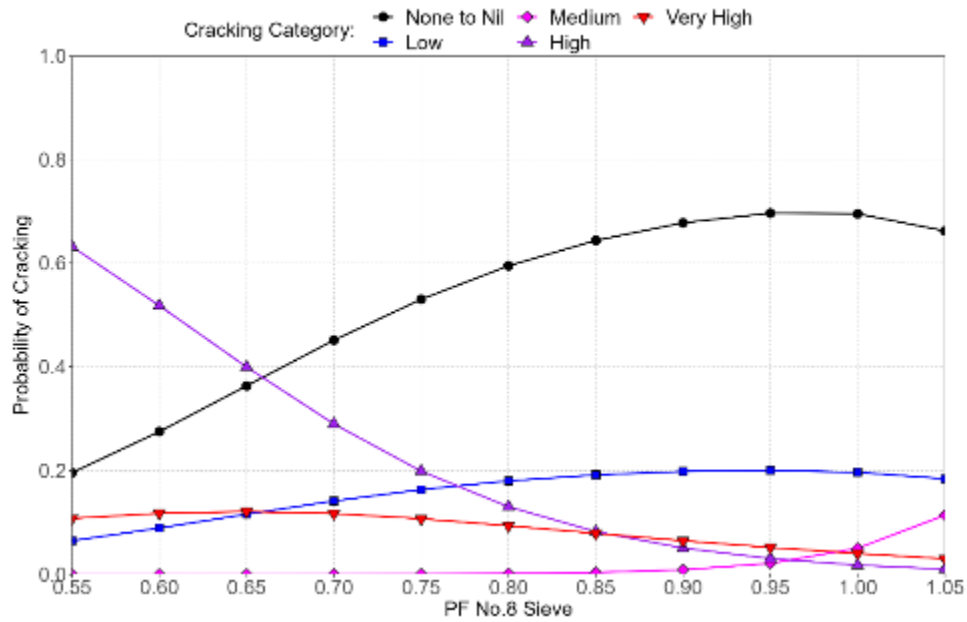


Figure I.4. Logistic Regression Predicted Probability of Cracking vs. P8 PF (Open Graded)

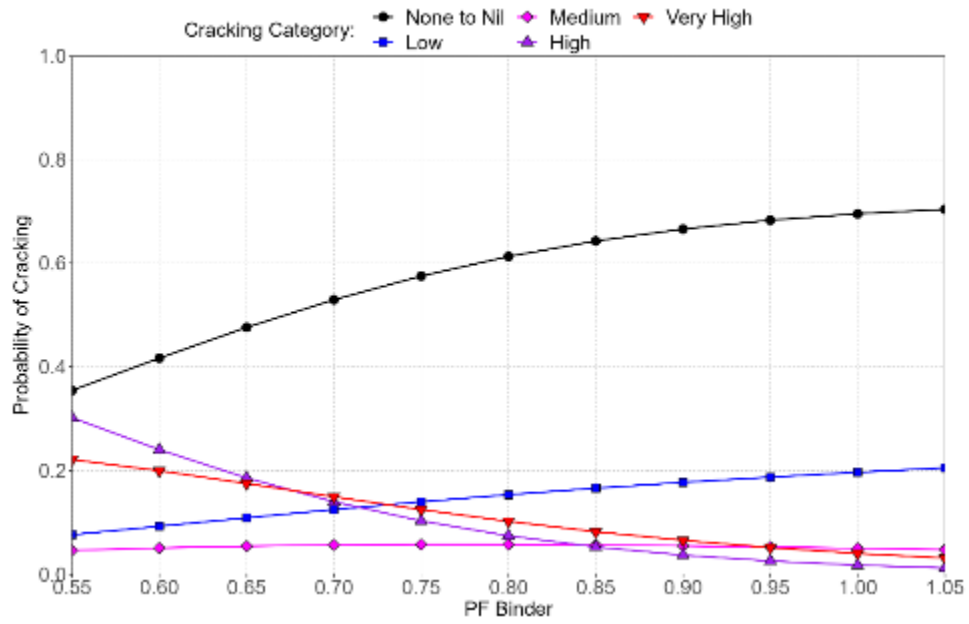


Figure I.5. Logistic Regression Predicted Probability of Cracking vs. Pb PF (Open Graded)

**APPENDIX J: MULTINOMIAL LOGISTIC ANALYSIS
FIGURES FOR RUTTING OF DENSE GRADED MIXTURES**

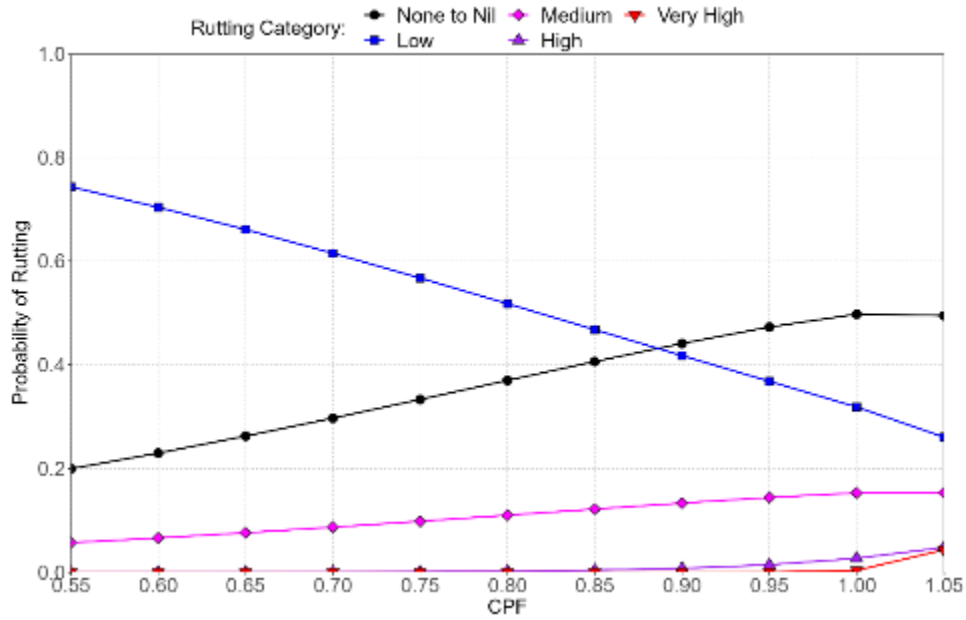


Figure J.1. Logistic Regression Predicted Probability of Rutting vs. CPF (Dense Graded)

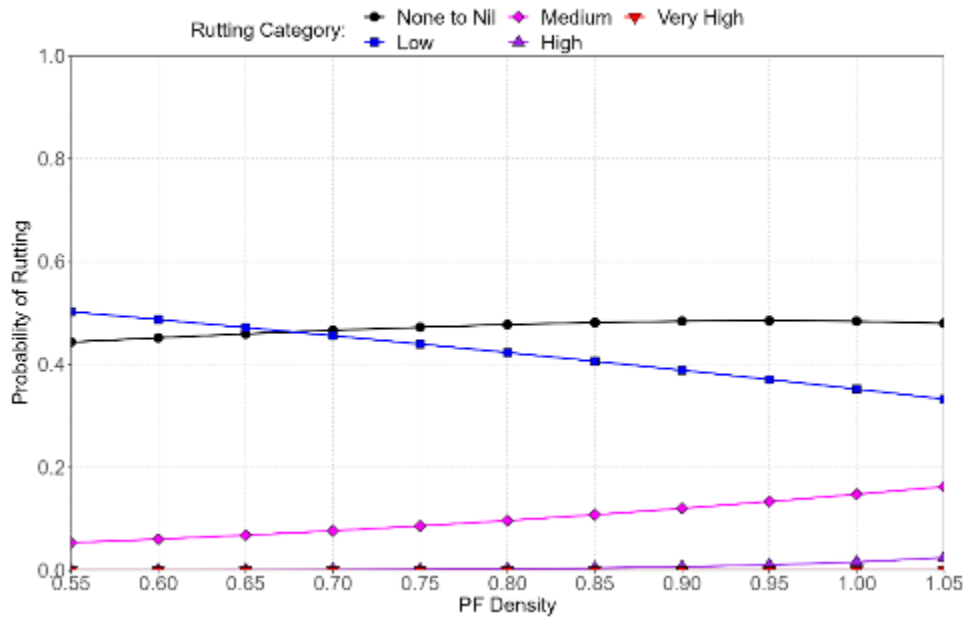


Figure J.2. Logistic Regression Predicted Probability of Rutting vs. Density PF (Dense Graded)

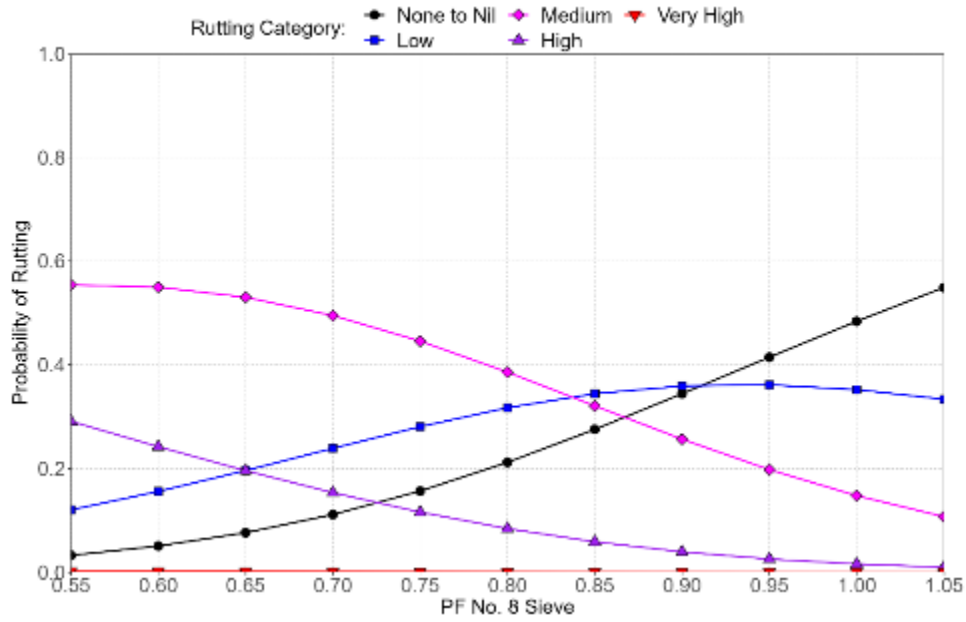


Figure J.3. Logistic Regression Predicted Probability of Rutting vs. P8 PF (Dense Graded)

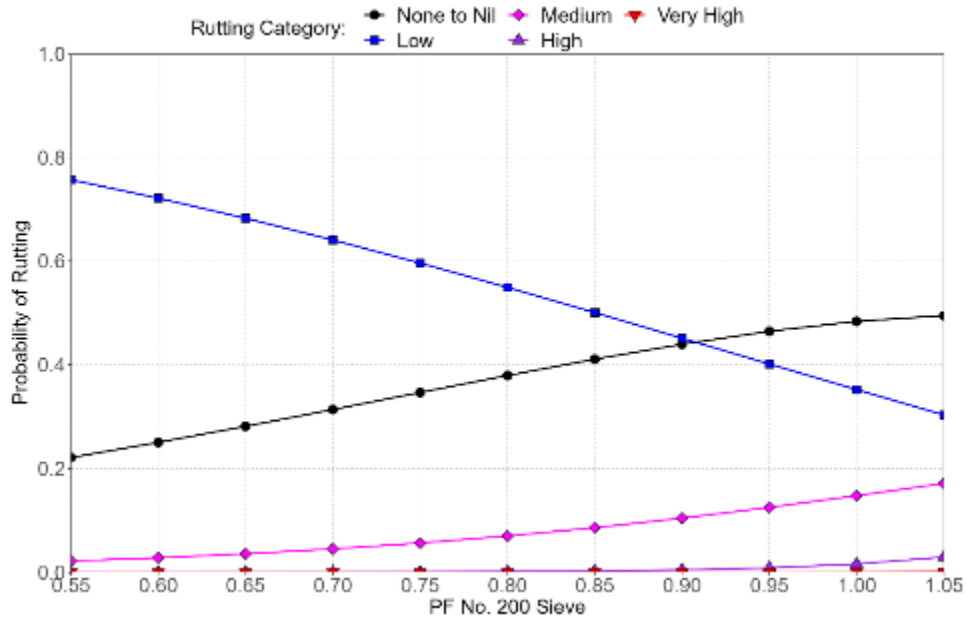


Figure J.4. Logistic Regression Predicted Probability of Rutting vs. P200 PF (Dense Graded)

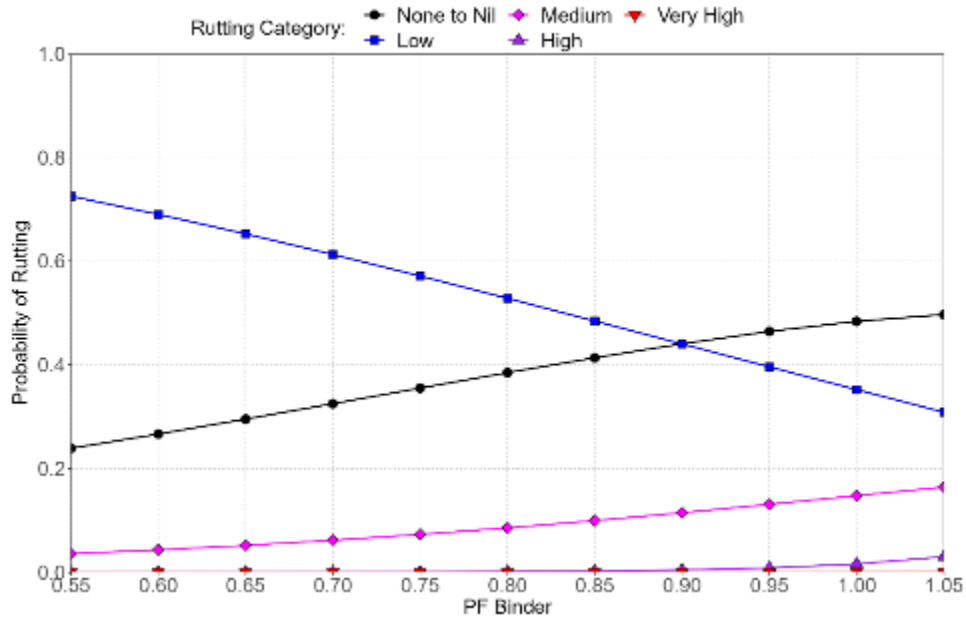


Figure J.5. Logistic Regression Predicted Probability of Rutting vs. Pb PF (Dense Graded)

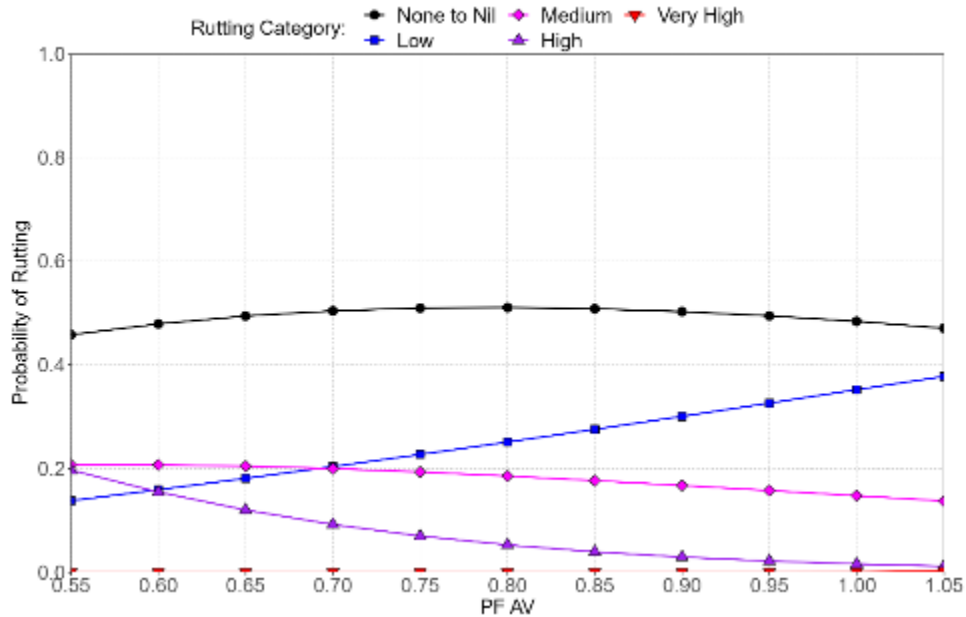


Figure J.6. Logistic Regression Predicted Probability of Rutting vs. Va PF (Dense Graded)

**APPENDIX K: MULTINOMIAL LOGISTIC ANALYSIS
FIGURES FOR RUTTING OF OPEN GRADED MIXTURES**

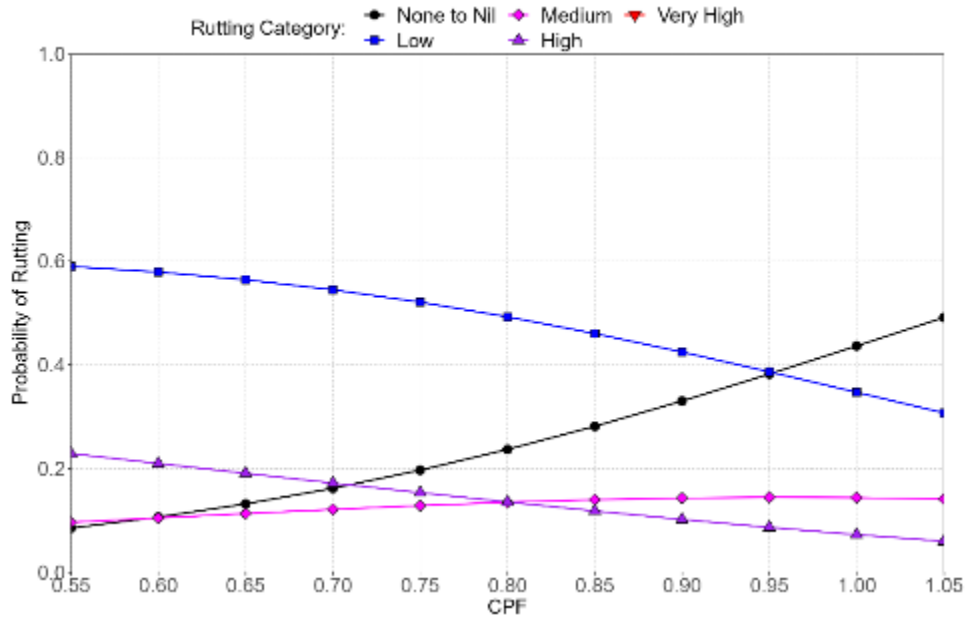


Figure K.1. Logistic Regression Predicted Probability of Rutting vs. CPF (Open Graded)

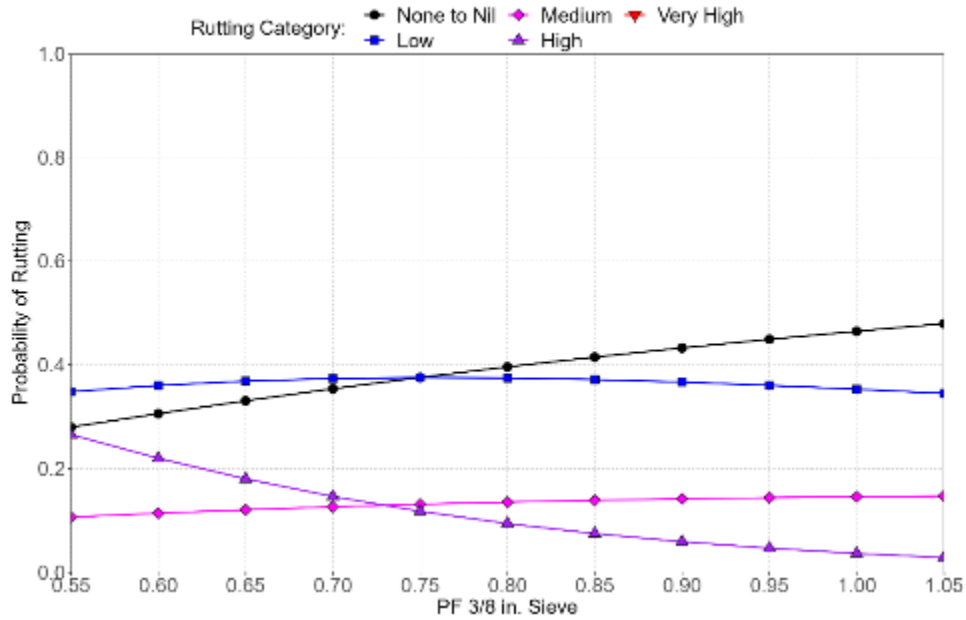


Figure K.2. Logistic Regression Predicted Probability of Rutting vs. P3.8 PF (Open Graded)

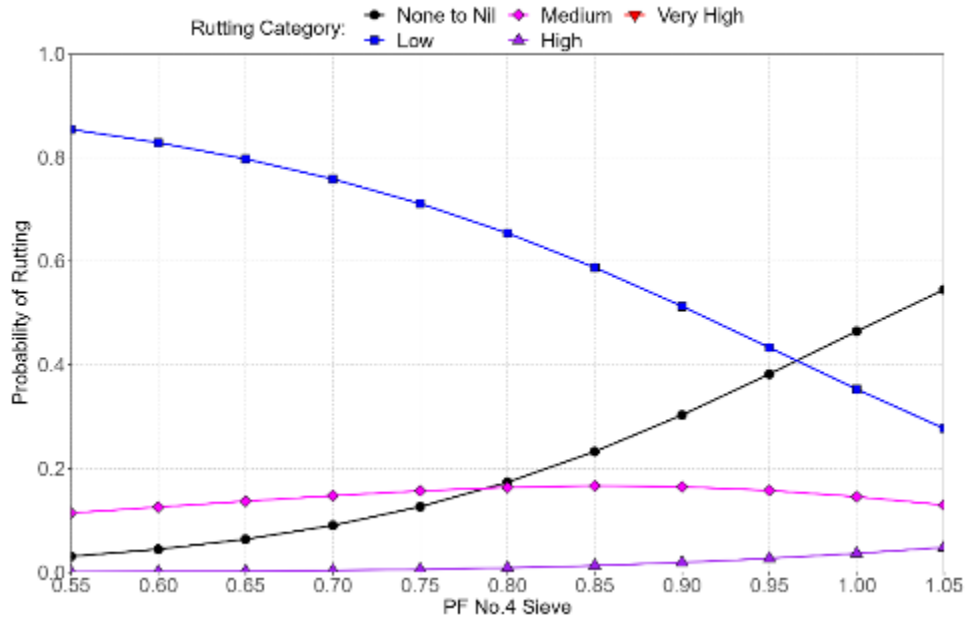


Figure K.3. Logistic Regression Predicted Probability of Rutting vs. P4 PF (Open Graded)

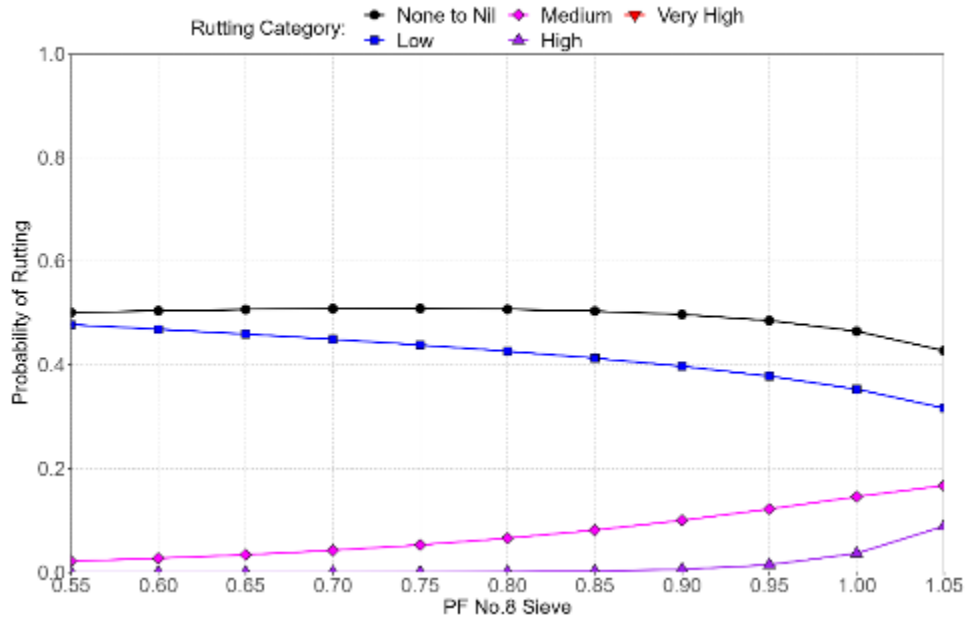


Figure K.4. Logistic Regression Predicted Probability of Rutting vs. P8 PF (Open Graded)

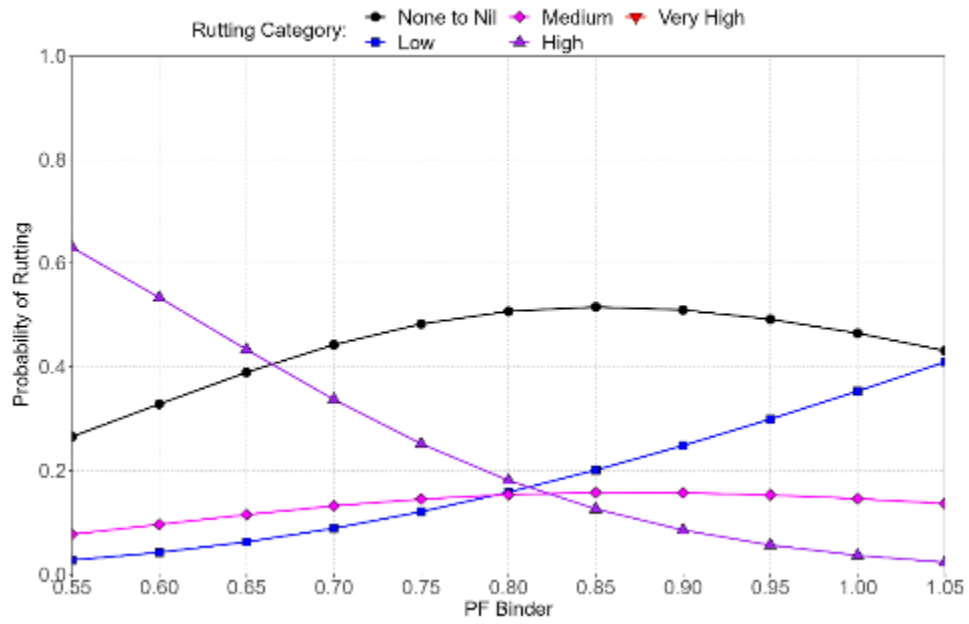


Figure K.5. Logistic Regression Predicted Probability of Rutting vs. Pb PF (Open Graded)

**APPENDIX L: MULTINOMIAL LOGISTIC ANALYSIS
FIGURES FOR RAVELING OF DENSE GRADED MIXTURES**

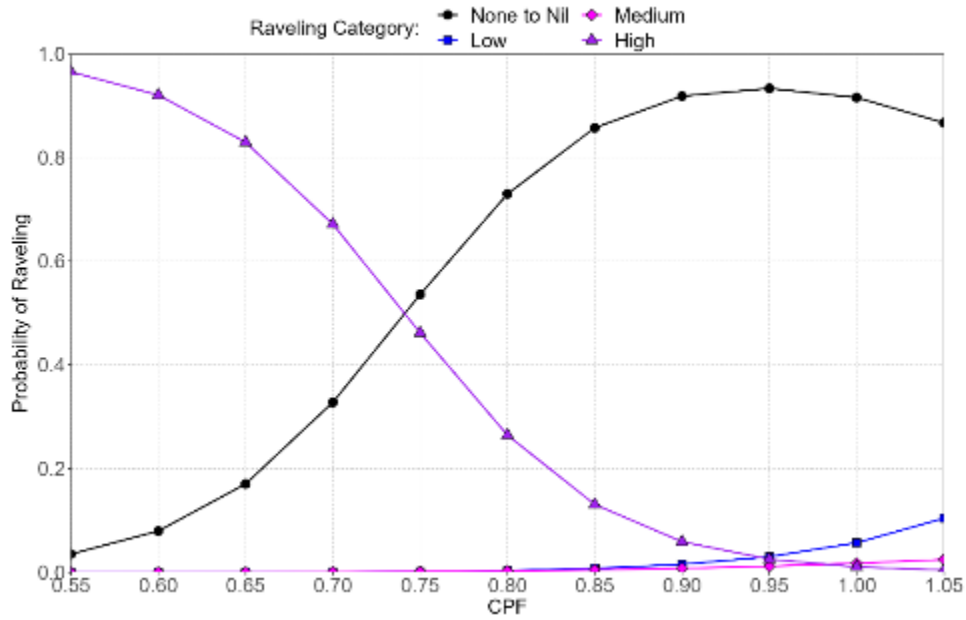


Figure L.1. Logistic Regression Predicted Probability of Raveling vs. CPF (Dense Graded)

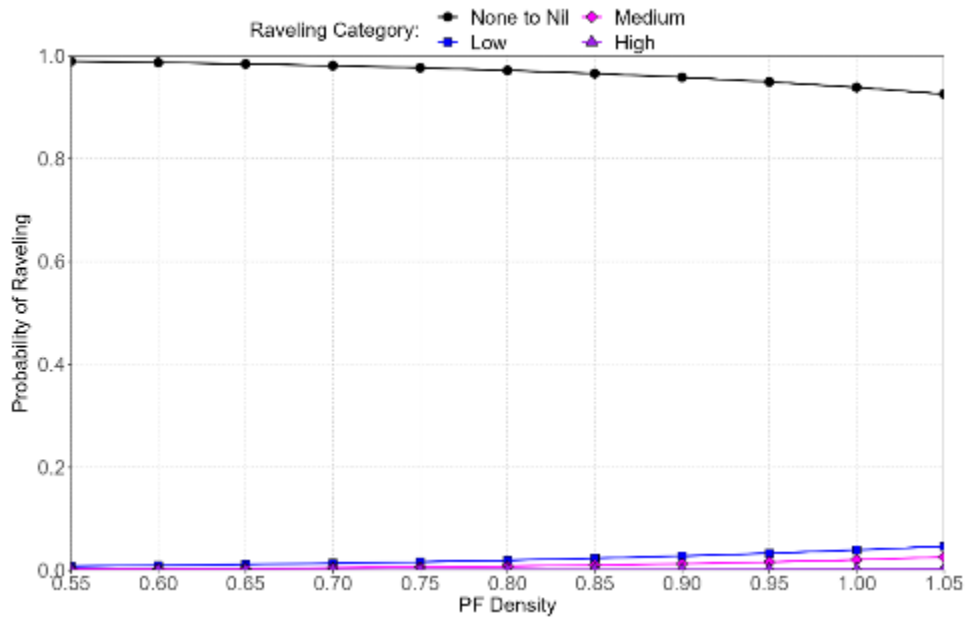


Figure L.2. Logistic Regression Predicted Probability of Raveling vs. Density PF (Dense Graded)

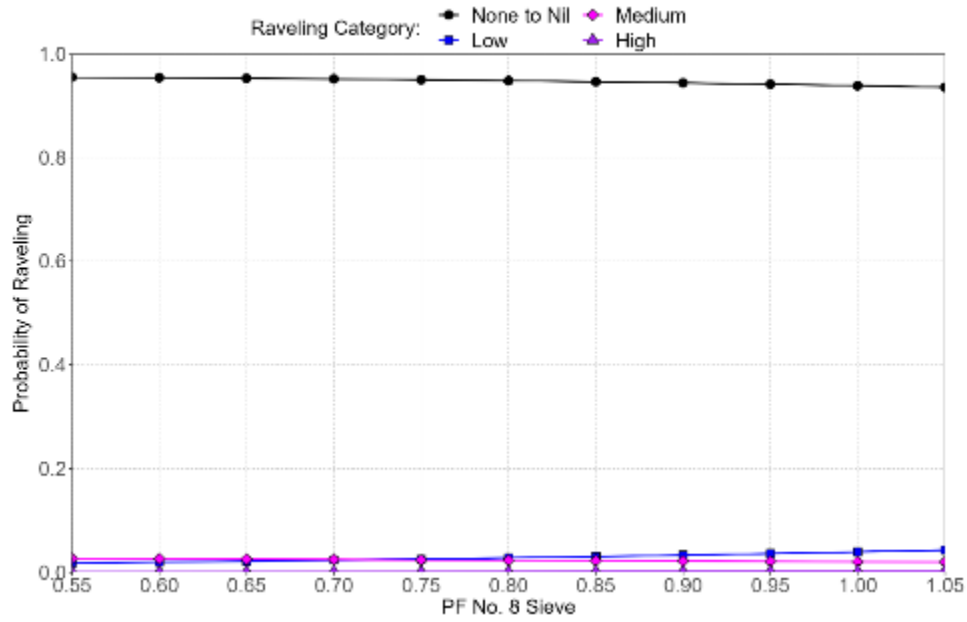


Figure L.3. Logistic Regression Predicted Probability of Raveling vs. P8 PF (Dense Graded)

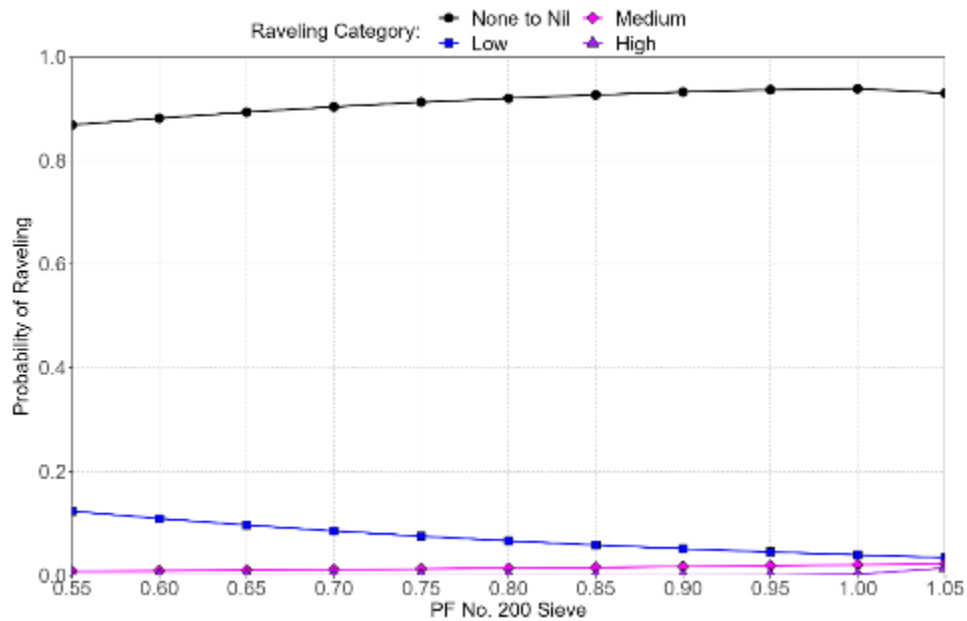


Figure L.4. Logistic Regression Predicted Probability of Raveling vs. P200 PF (Dense Graded)

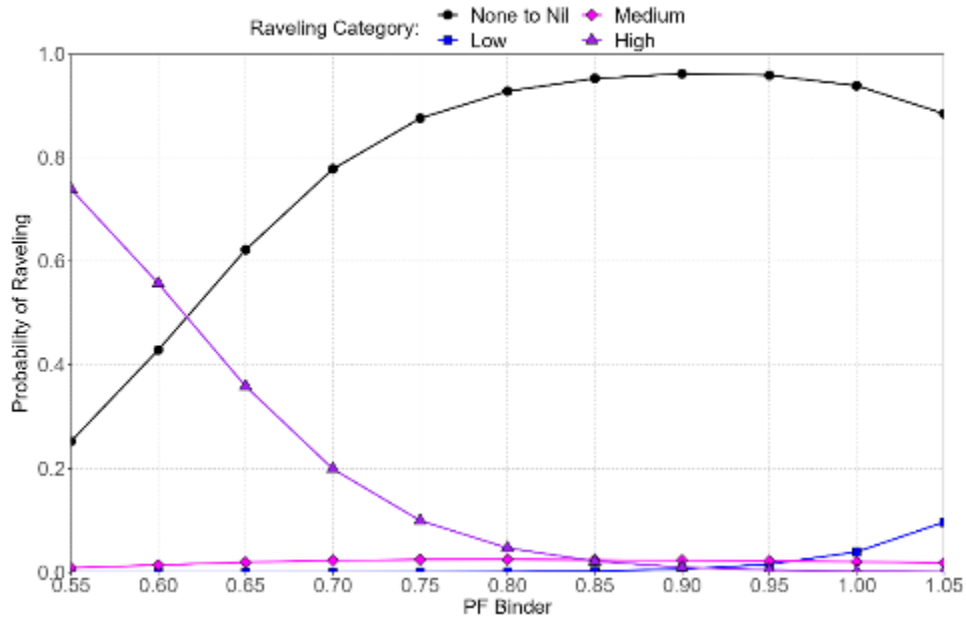


Figure L.5. Logistic Regression Predicted Probability of Raveling vs. Pb PF (Dense Graded)

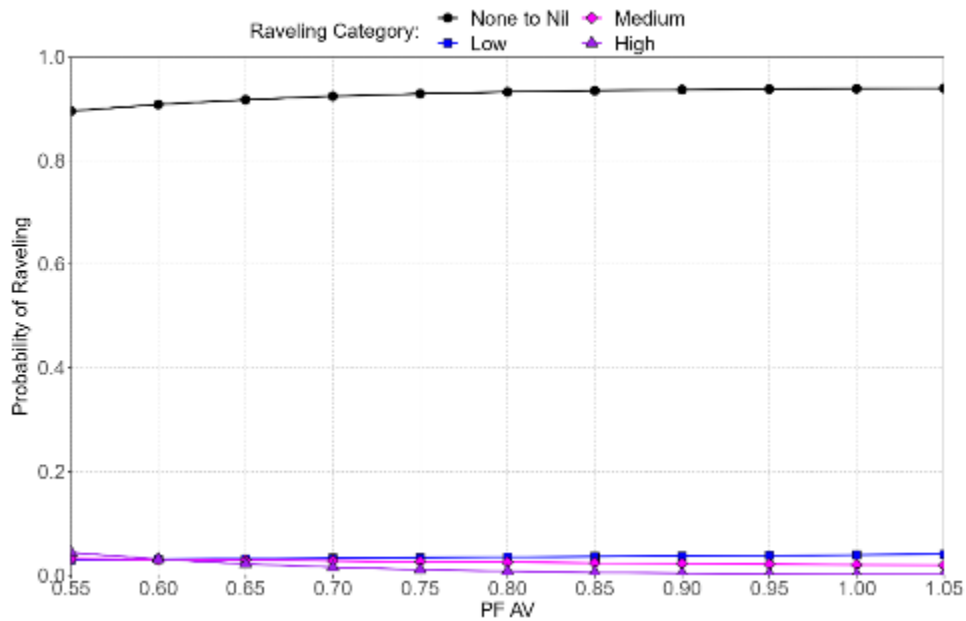


Figure L.6. Logistic Regression Predicted Probability of Raveling vs. Va PF (Dense Graded)

**APPENDIX M: MULTINOMIAL LOGISTIC ANALYSIS
FIGURES FOR RAVELING OF OPEN GRADED MIXTURES**

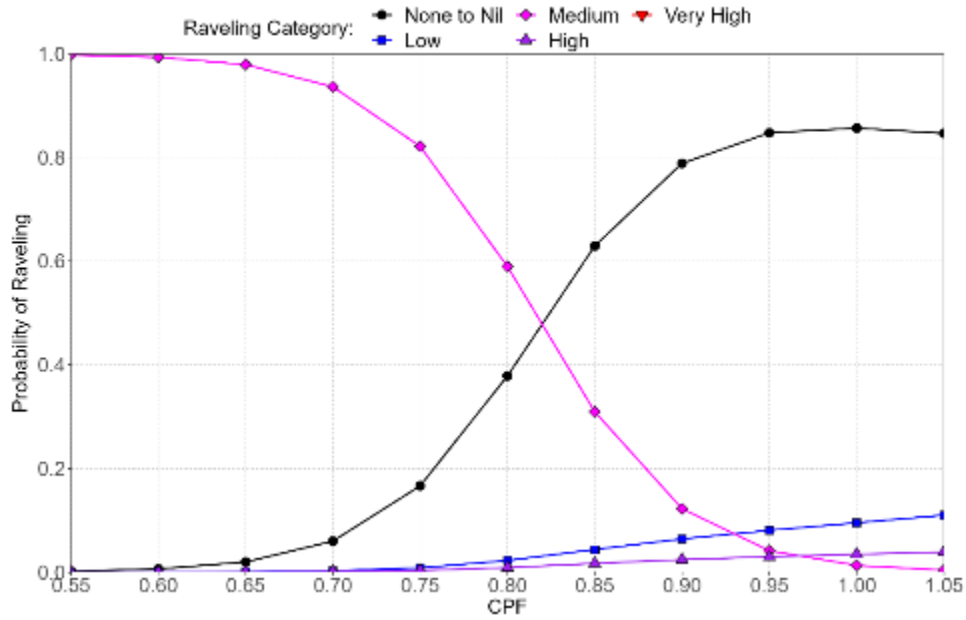


Figure M.1. Logistic Regression Predicted Probability of Raveling vs. CPF (Open Graded)

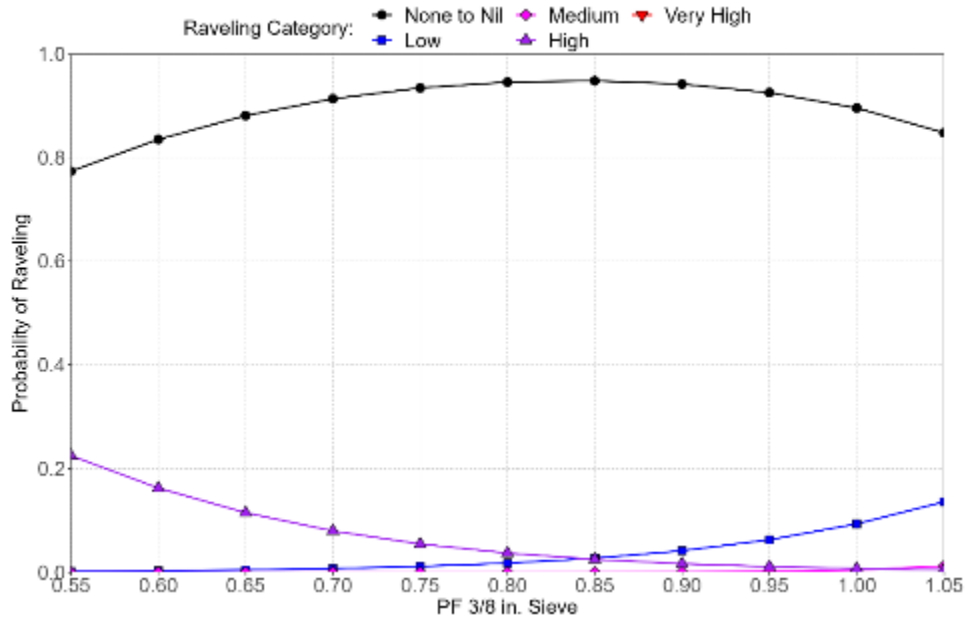


Figure M.2. Logistic Regression Predicted Probability of Raveling vs. P3.8 PF (Open Graded)

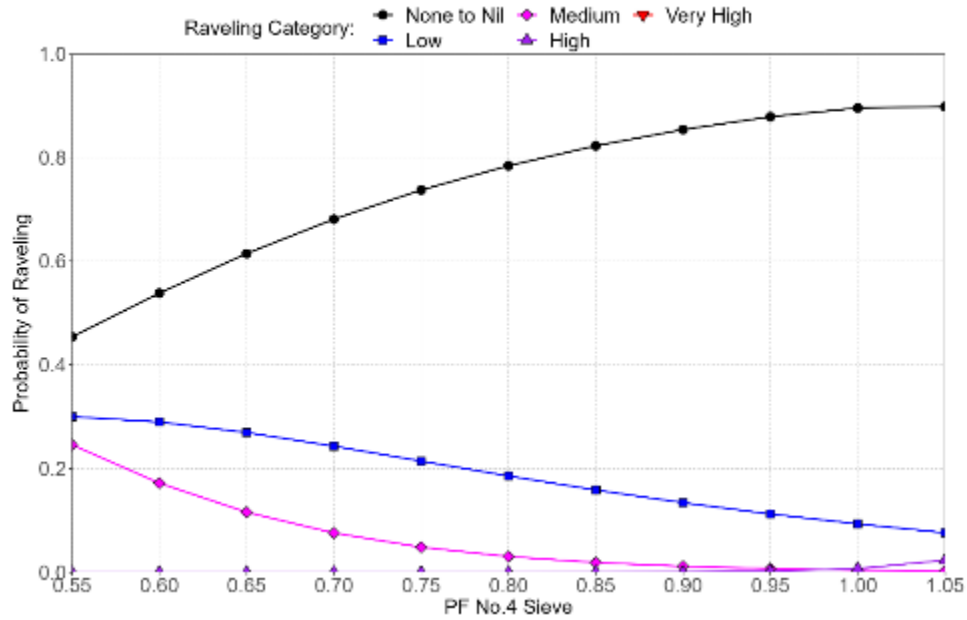


Figure M.3. Logistic Regression Predicted Probability of Raveling vs. P4 PF (Open Graded)

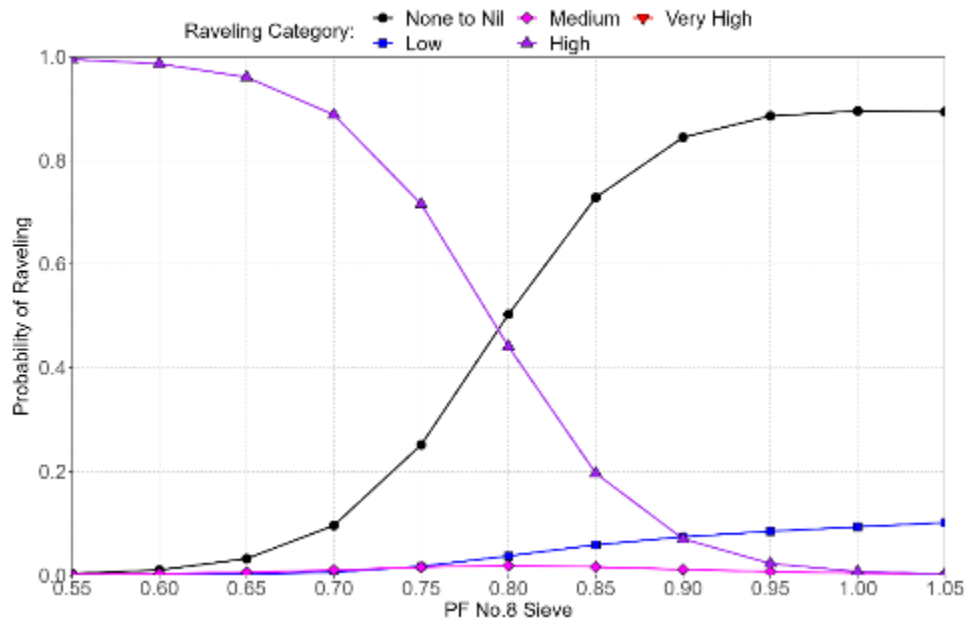


Figure M.4. Logistic Regression Predicted Probability of Raveling vs. P8 PF (Open Graded)

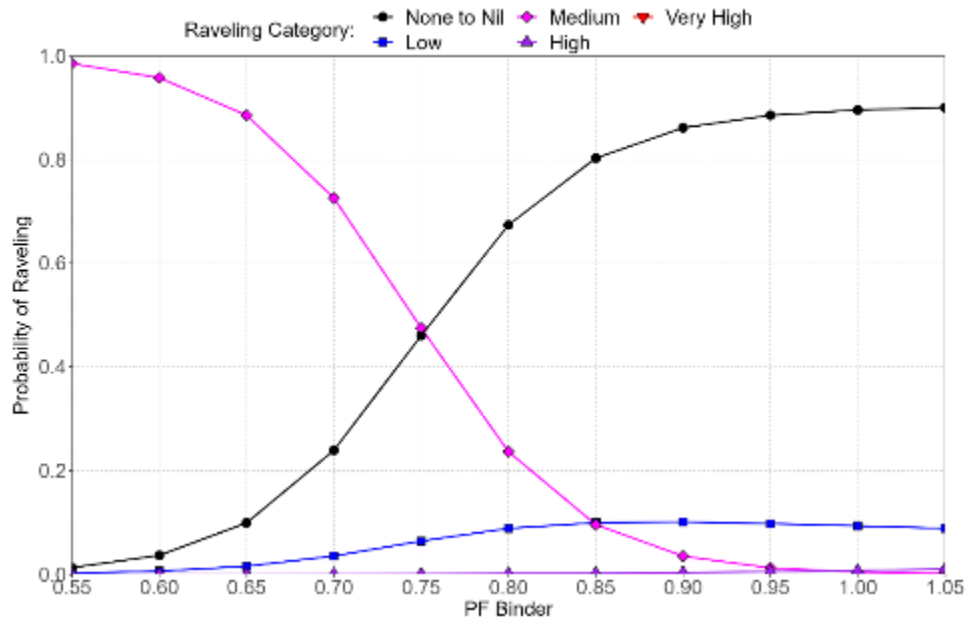


Figure M.5. Logistic Regression Predicted Probability of Raveling vs. Pb PF (Open Graded)

**APPENDIX N: SIMULATED PROBABILITY CURVES FOR
CRACKING OF DENSE GRADED MIXTURES**

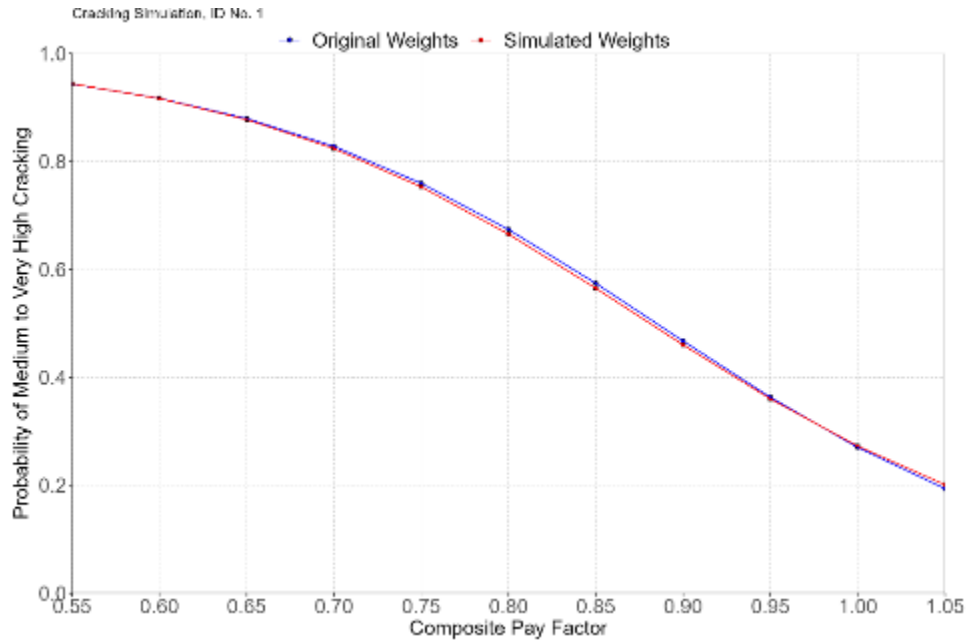


Figure N.1 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 1)

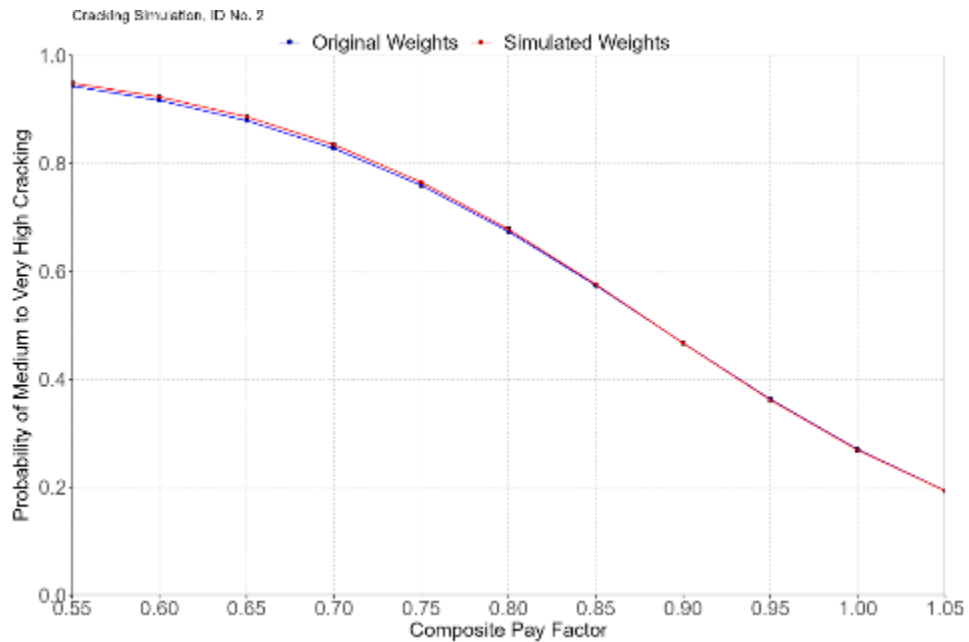


Figure N.2 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 2)

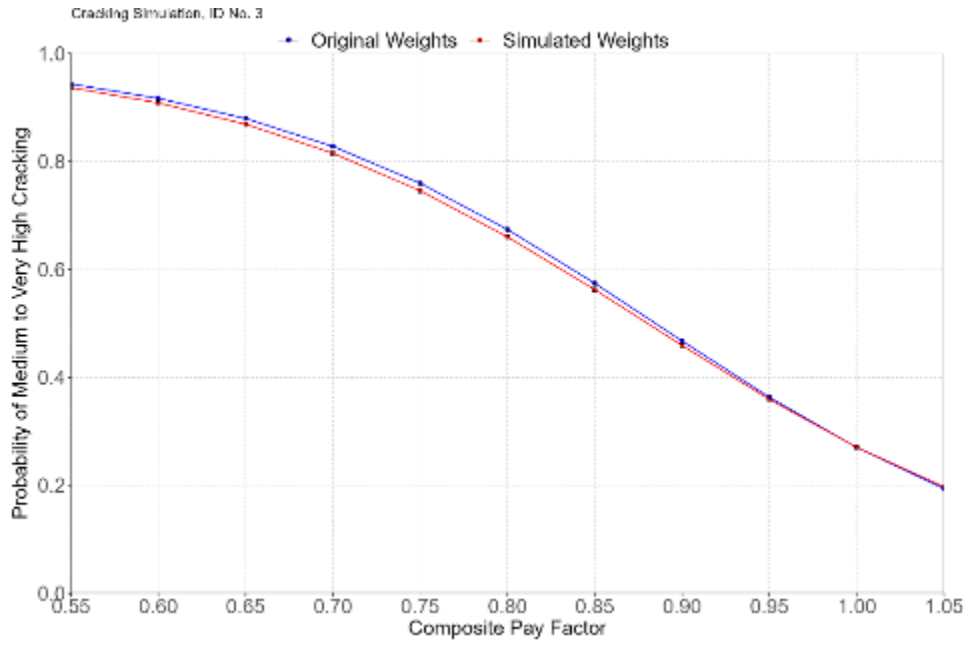


Figure N.3 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 3)

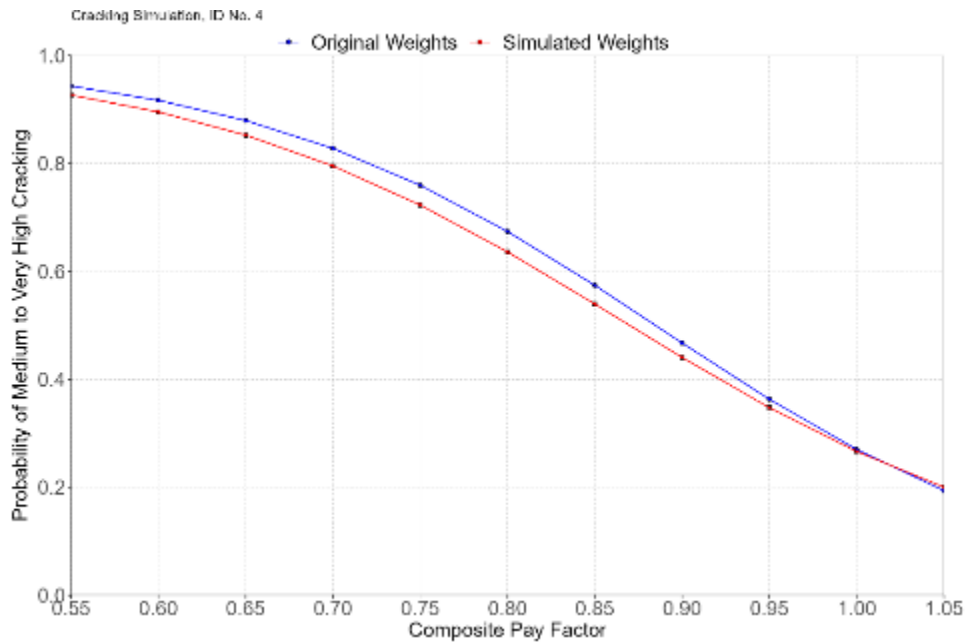


Figure N.4 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 4)

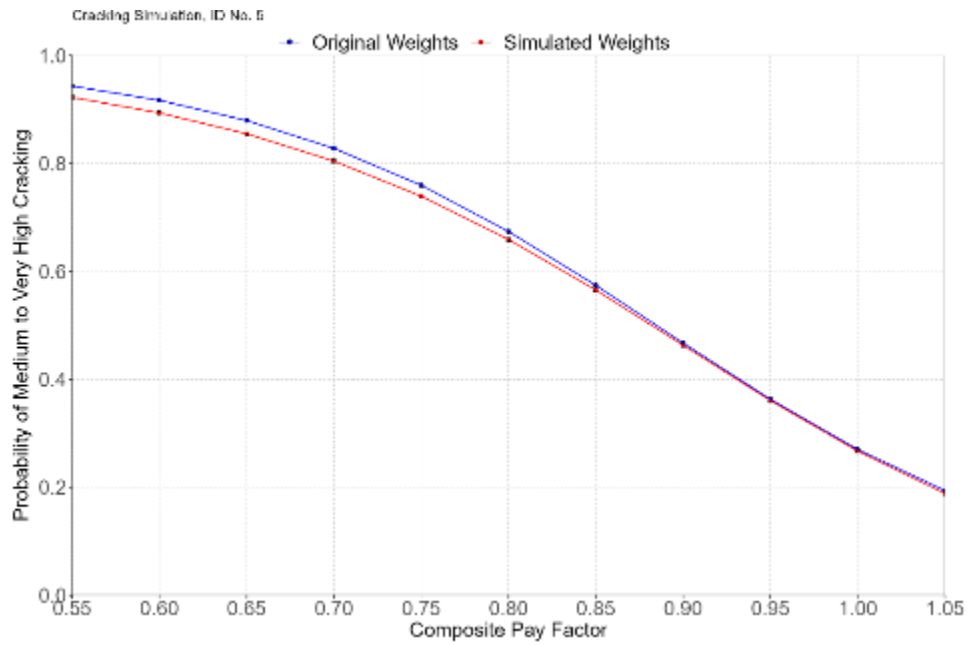


Figure N.5 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 5)

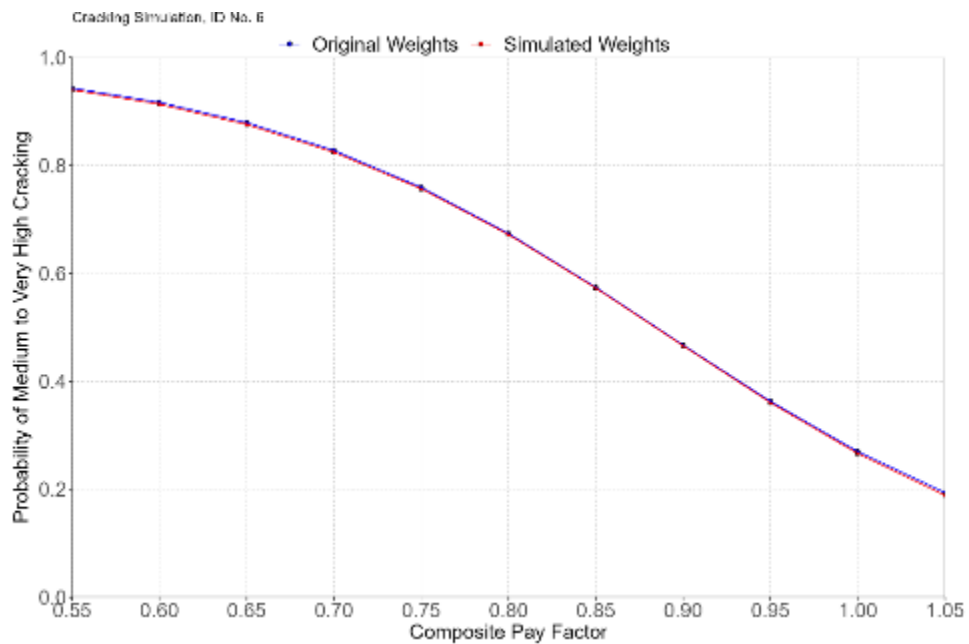


Figure N.6 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 6)

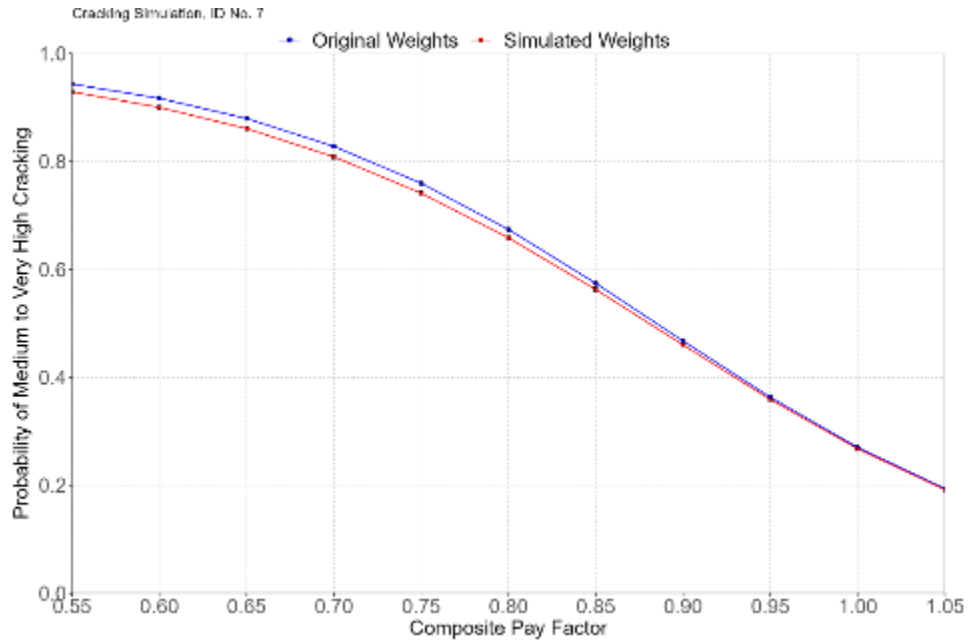


Figure N.7 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 7)

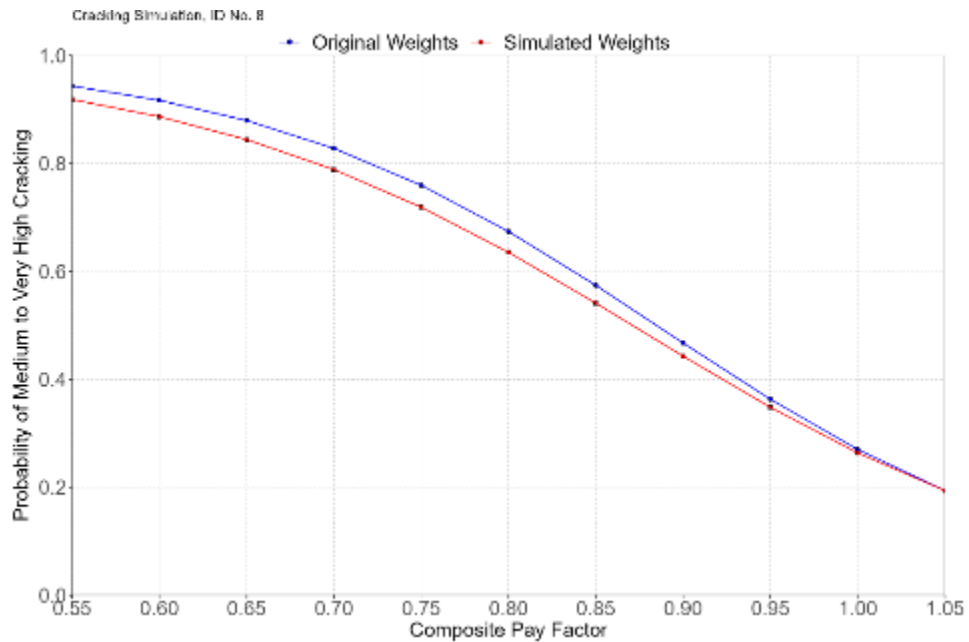


Figure N.8 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 8)

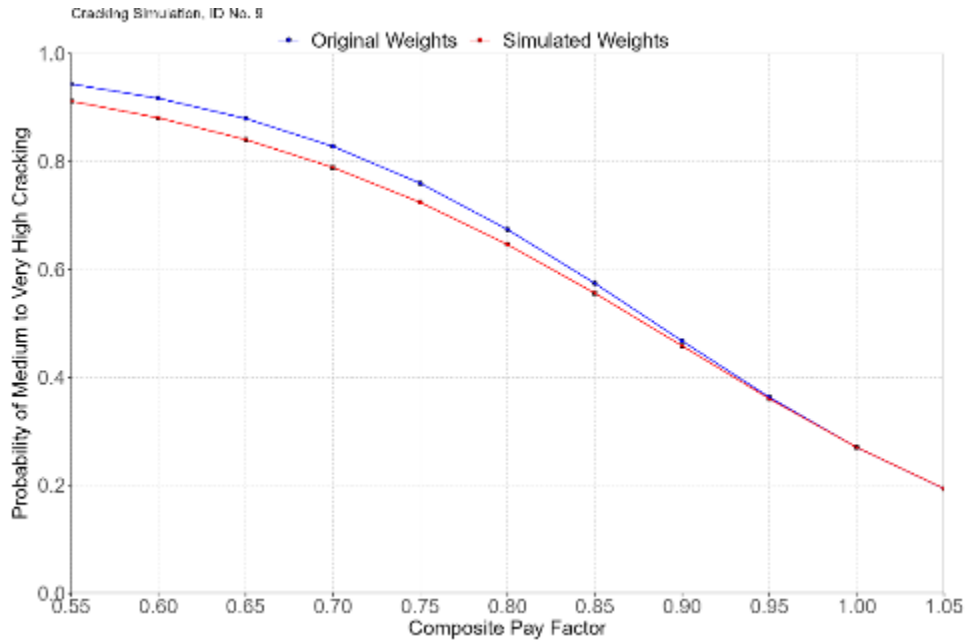


Figure N.9 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 9)

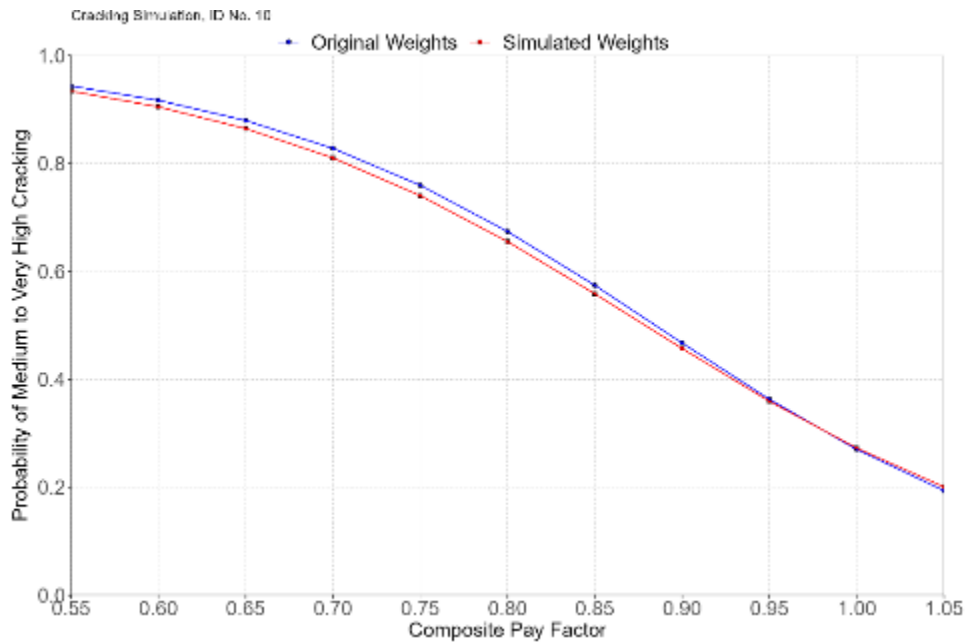


Figure N.10 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 10)

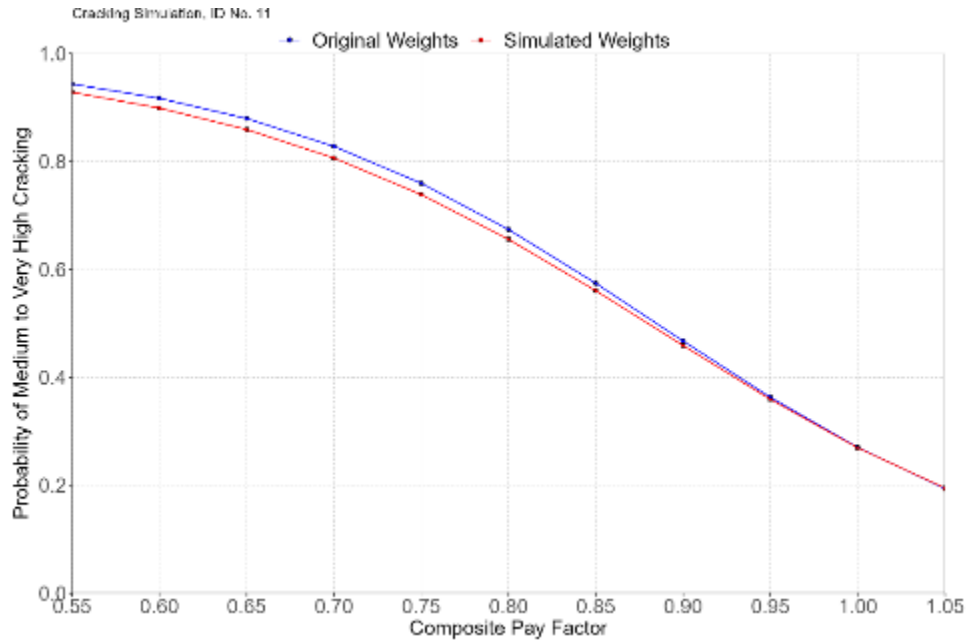


Figure N.11 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 11)

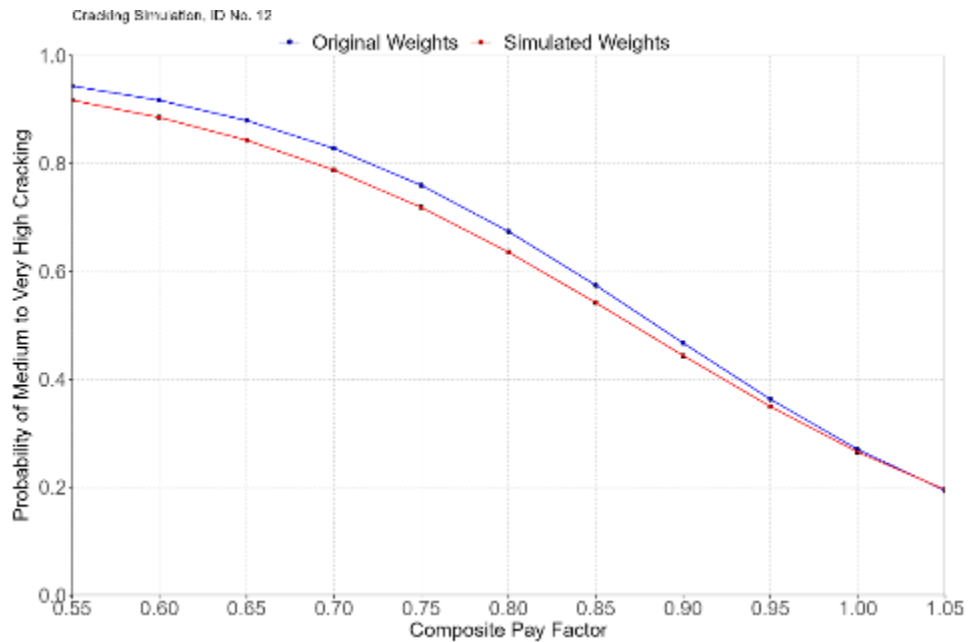


Figure N.12 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 12)

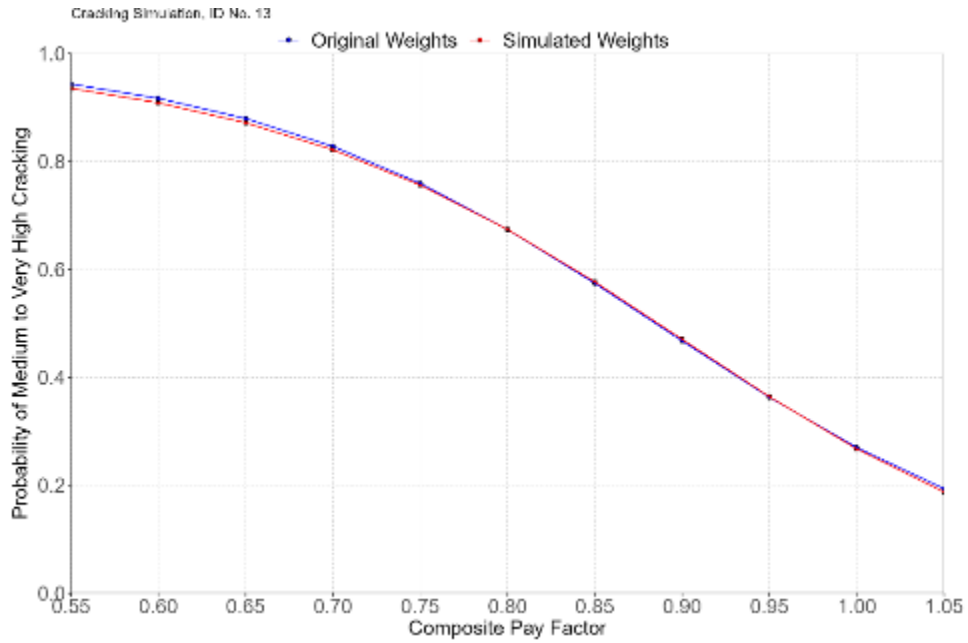


Figure N.13 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 13)

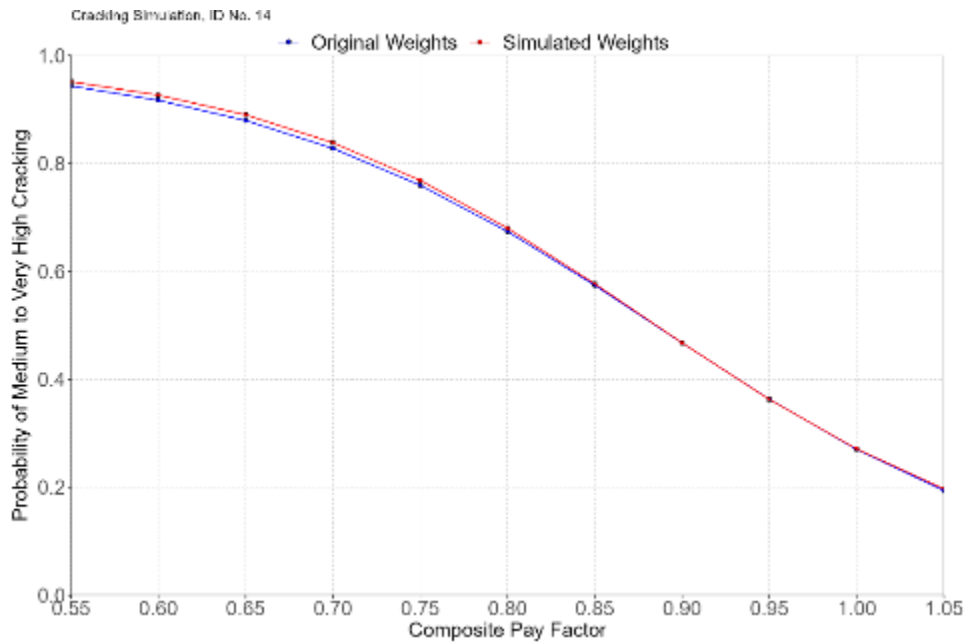


Figure N.14 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 14)

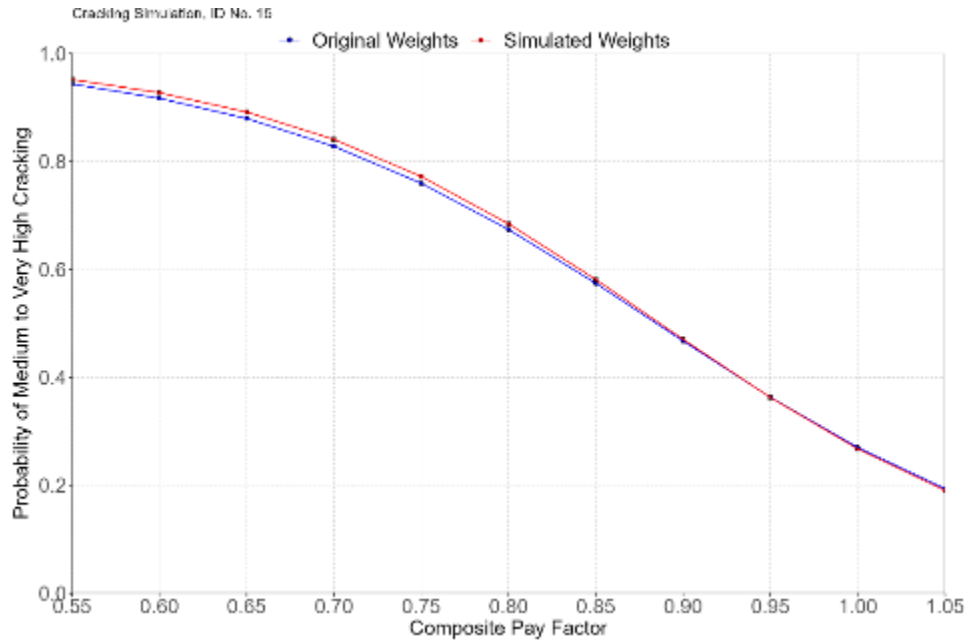


Figure N.15 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 15)

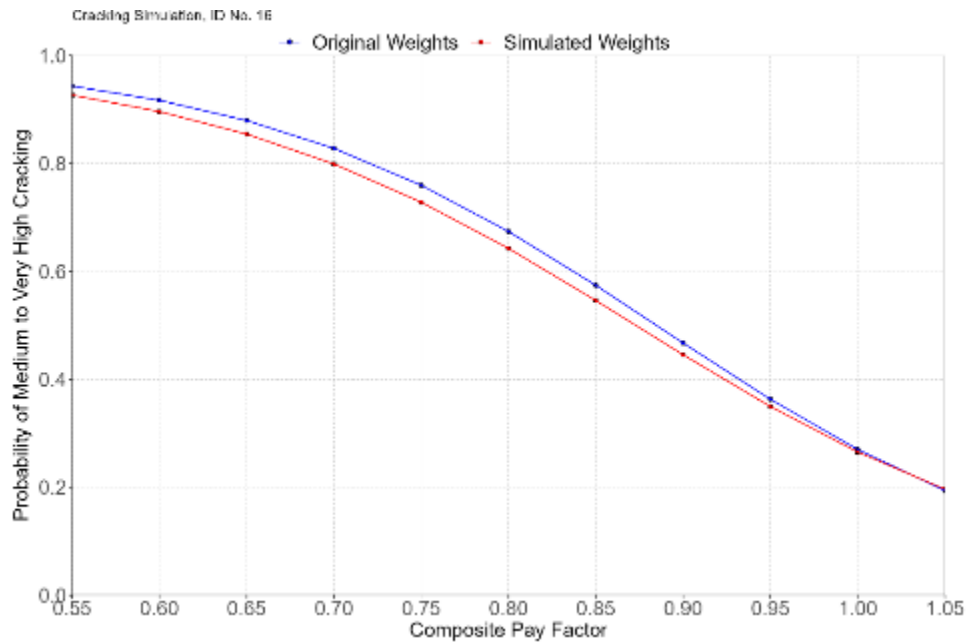


Figure N.16 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 16)

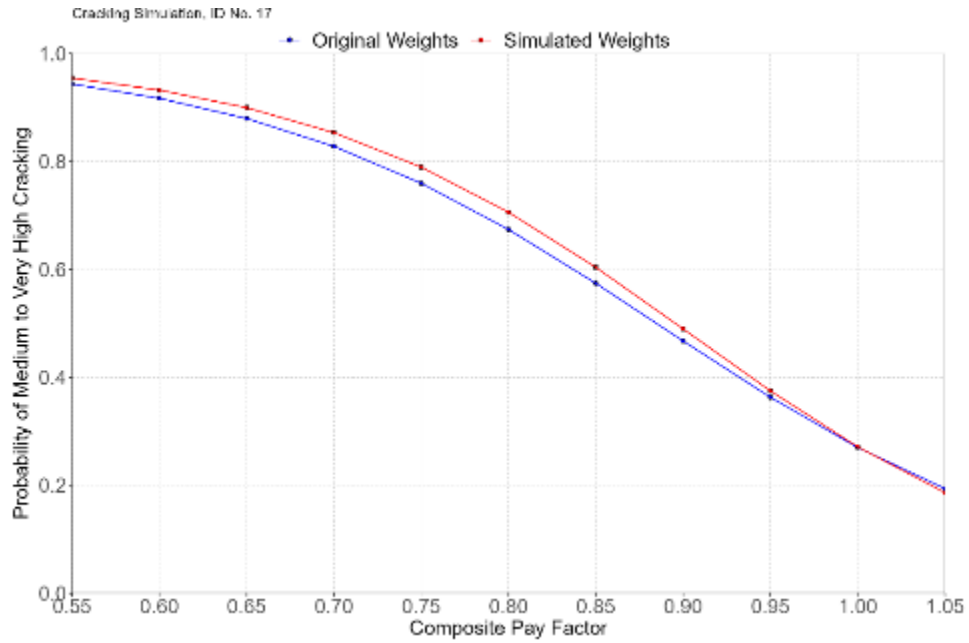


Figure N.17 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 17)

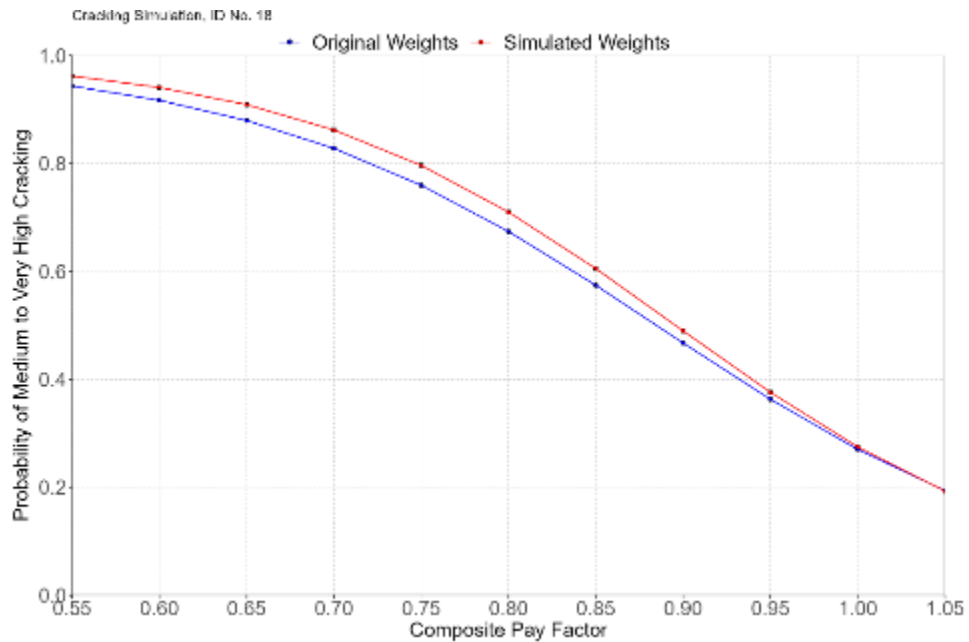


Figure N.18 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 18)

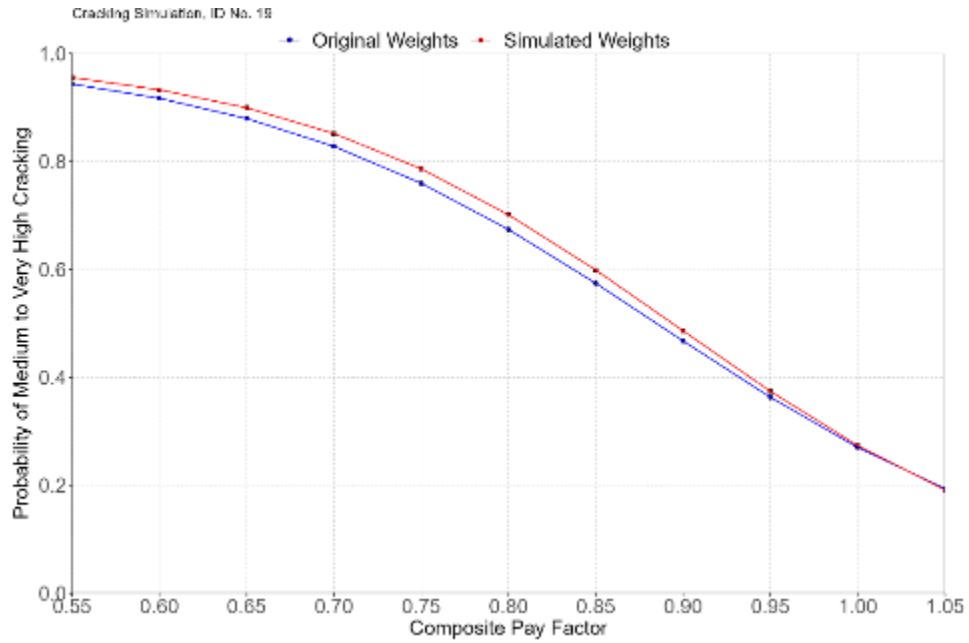


Figure N.19 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 19)

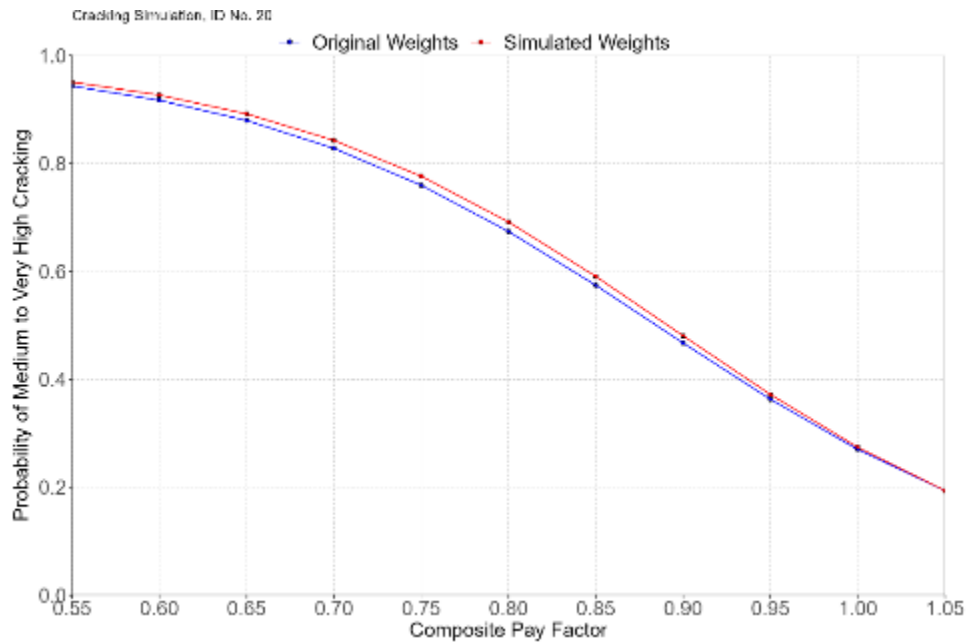


Figure N.20 Cracking Probability Curves for Dense Graded Mixtures (Simulation ID 20)

**APPENDIX O: SIMULATED PROBABILITY CURVES FOR
RUTTING OF DENSE GRADED MIXTURES**

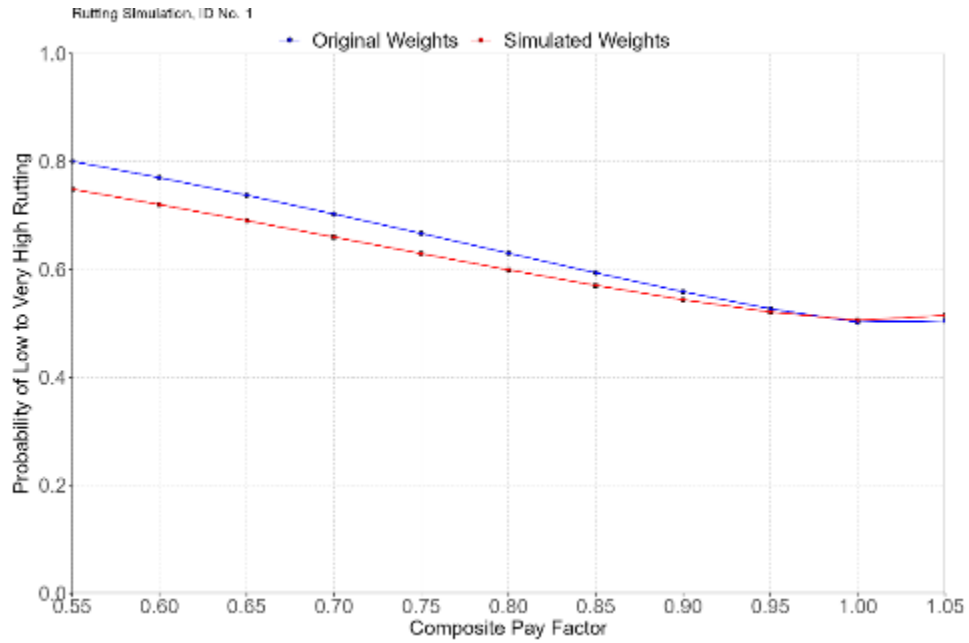


Figure O.1 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 1)

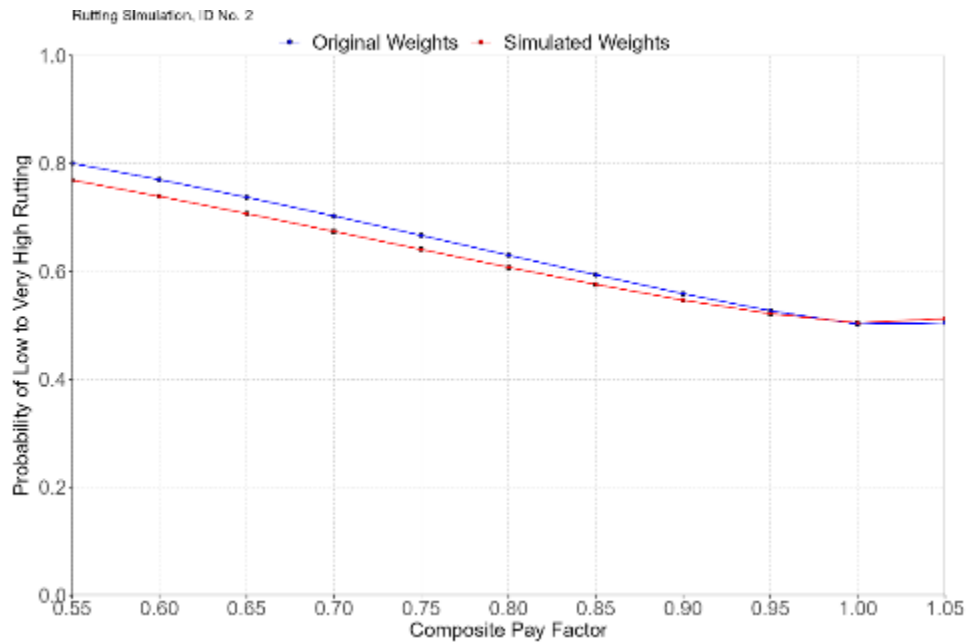


Figure O.2 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 2)

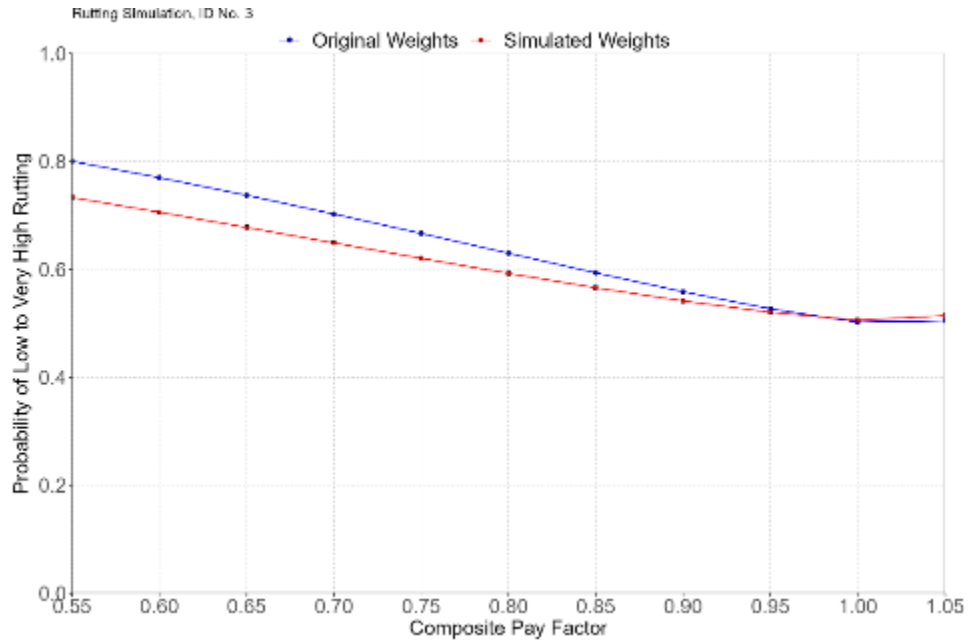


Figure O.3 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 3)

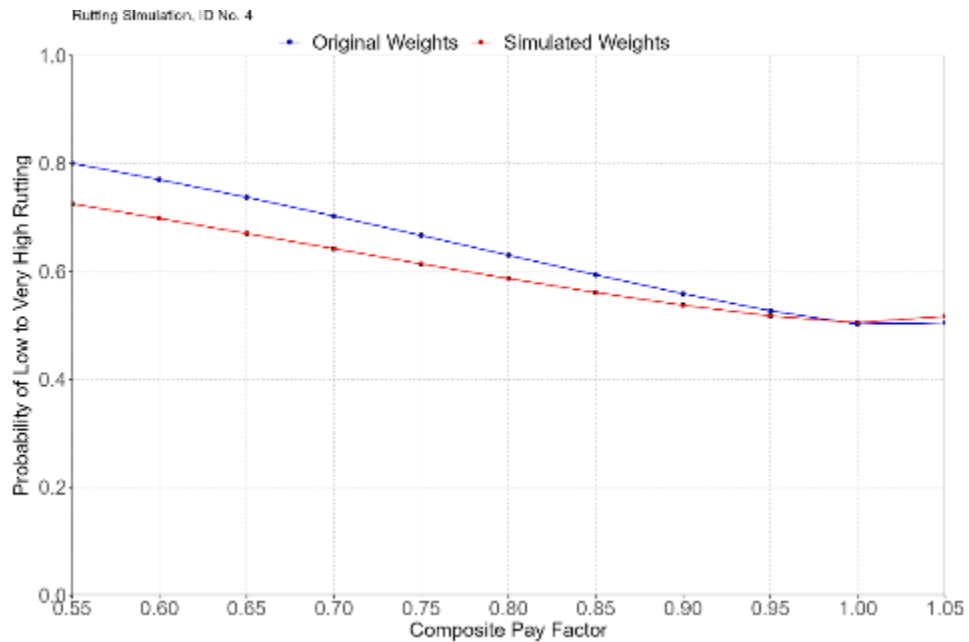


Figure O.4 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 4)

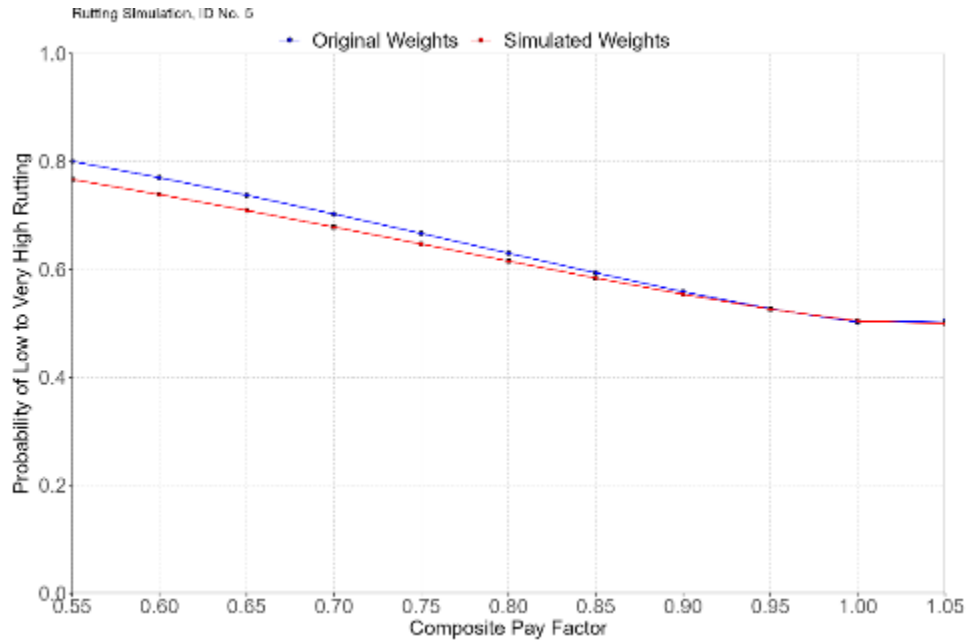


Figure O.5 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 5)

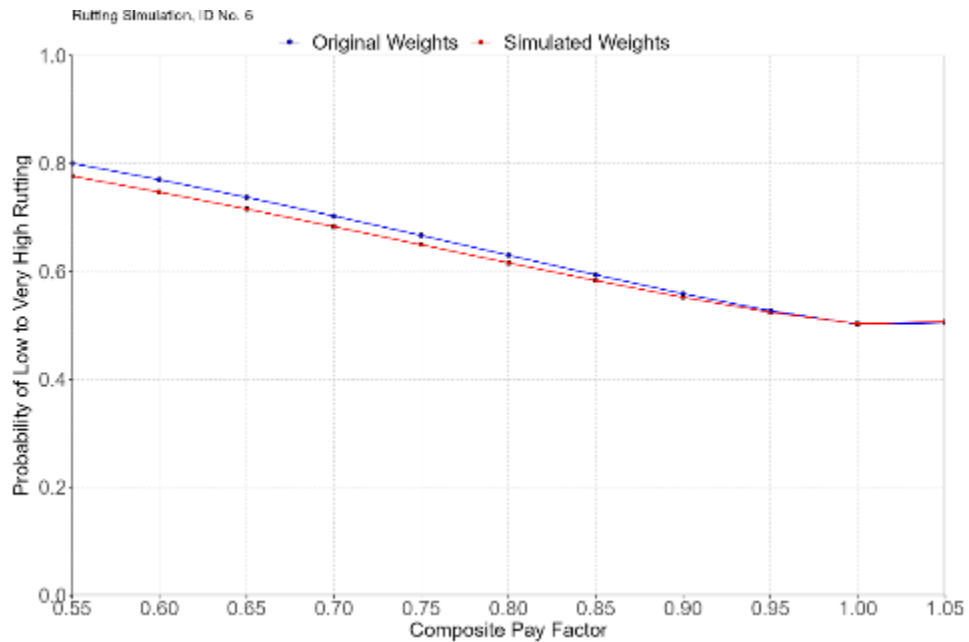


Figure O.6 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 6)

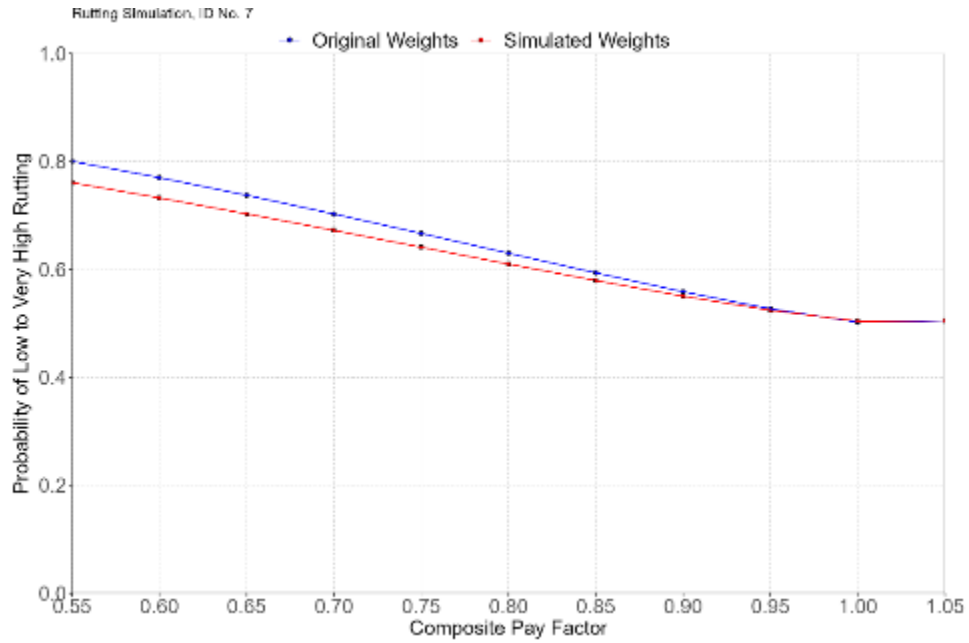


Figure O.7 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 7)

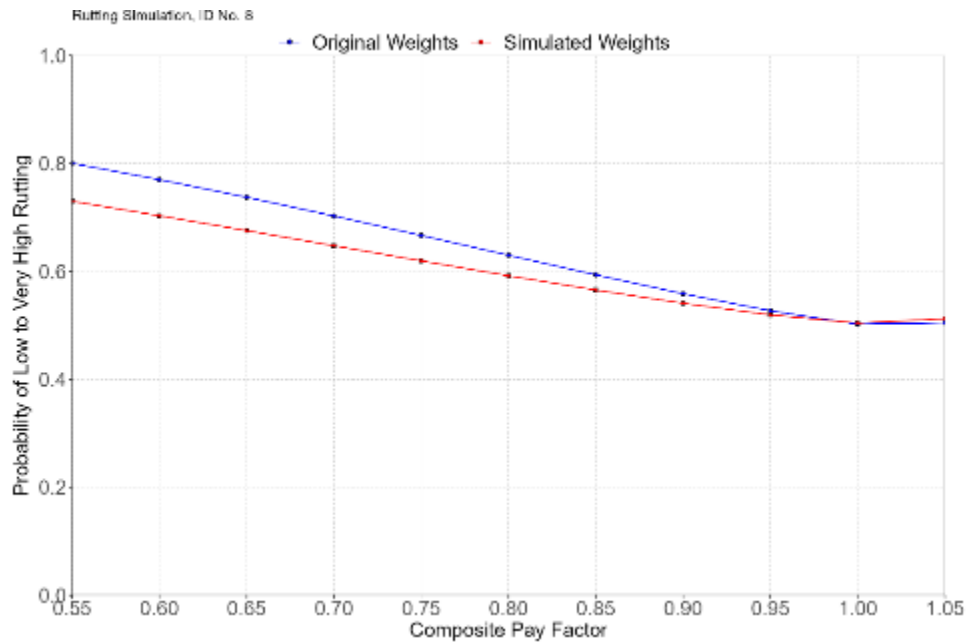


Figure O.8 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 8)

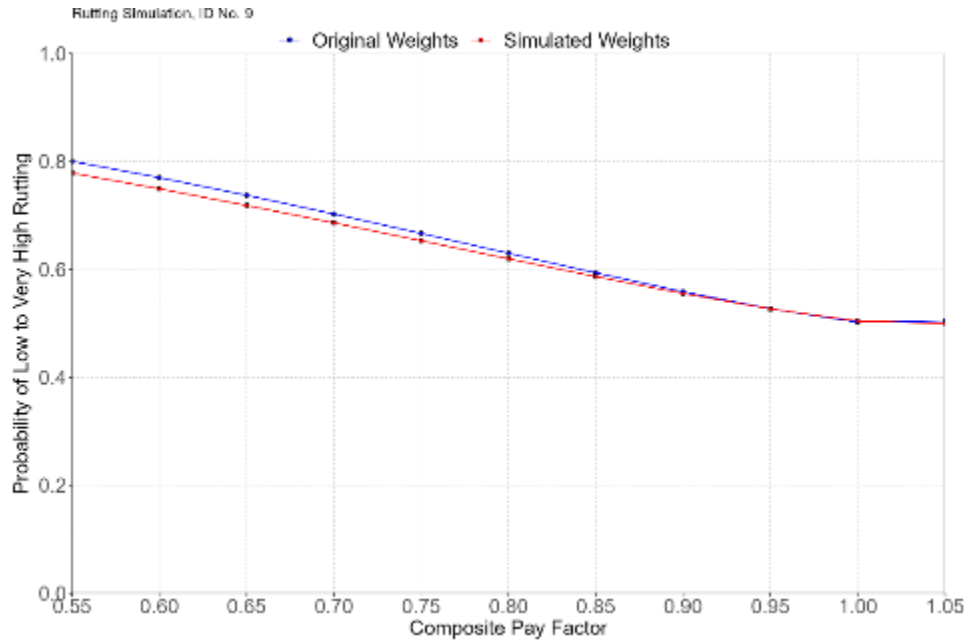


Figure O.9 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 9)

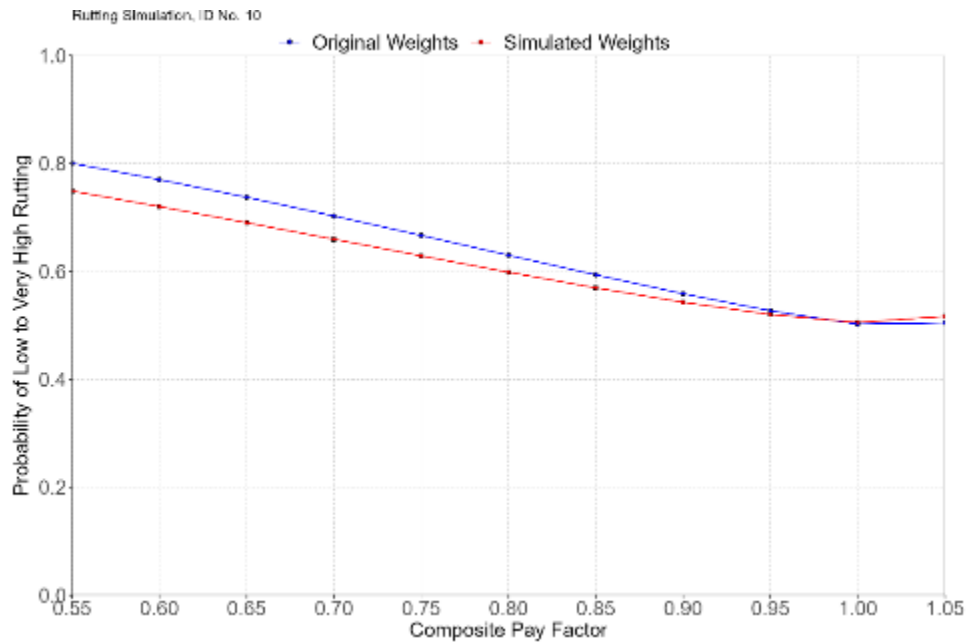


Figure O.10 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 10)

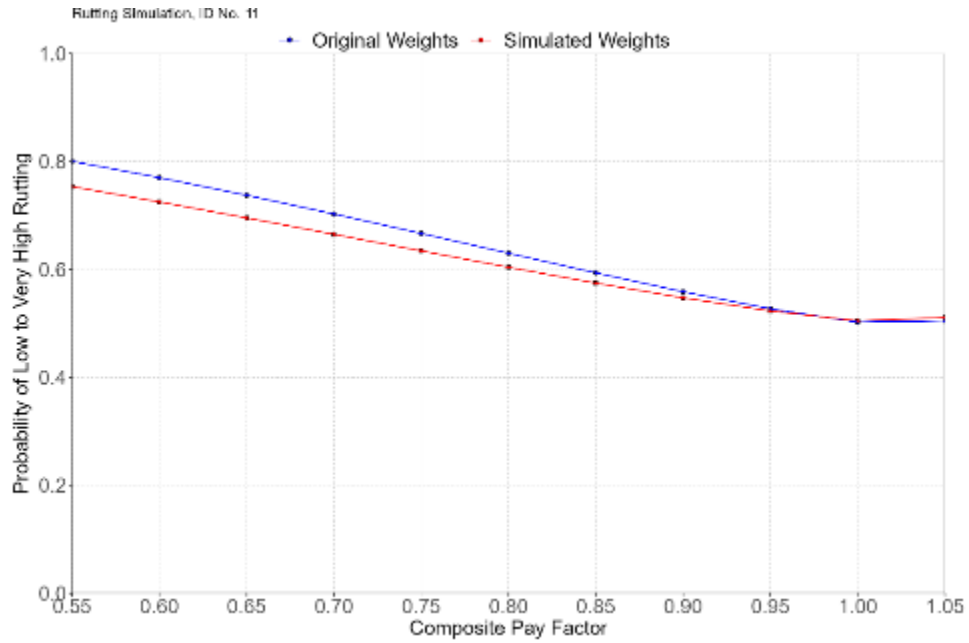


Figure O.11 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 11)

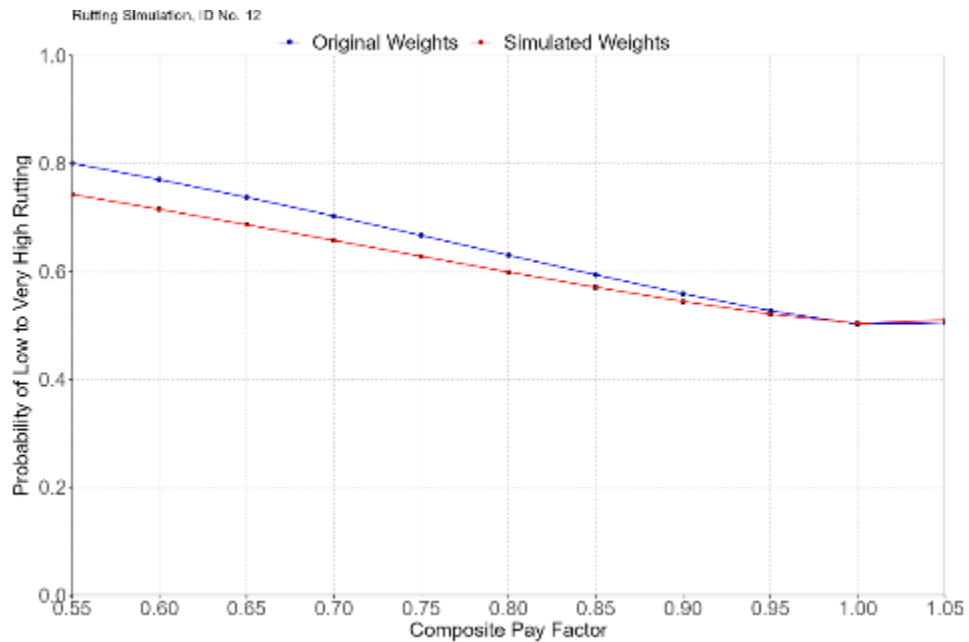


Figure O.12 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 12)

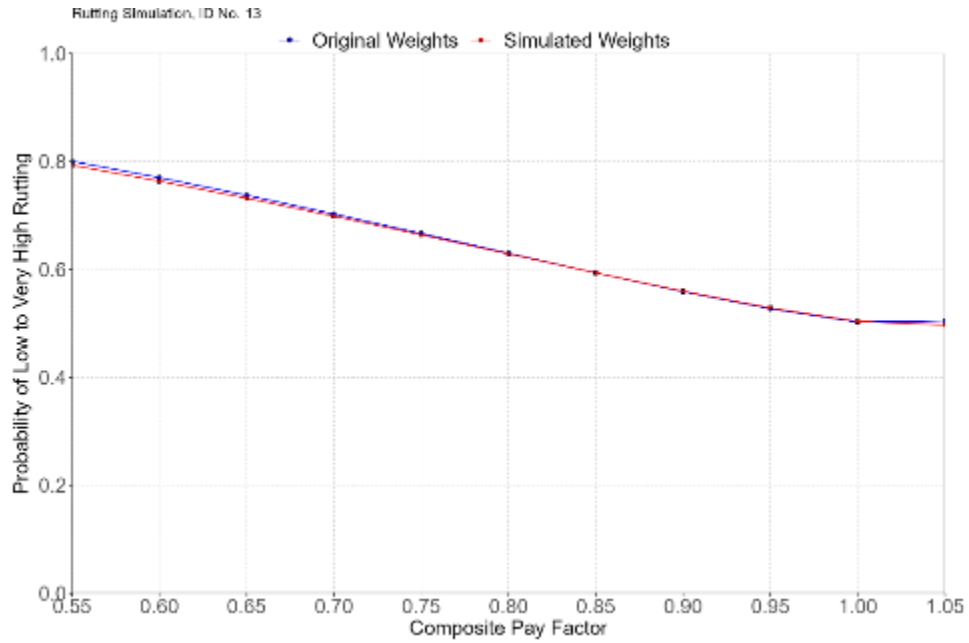


Figure O.13 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 13)

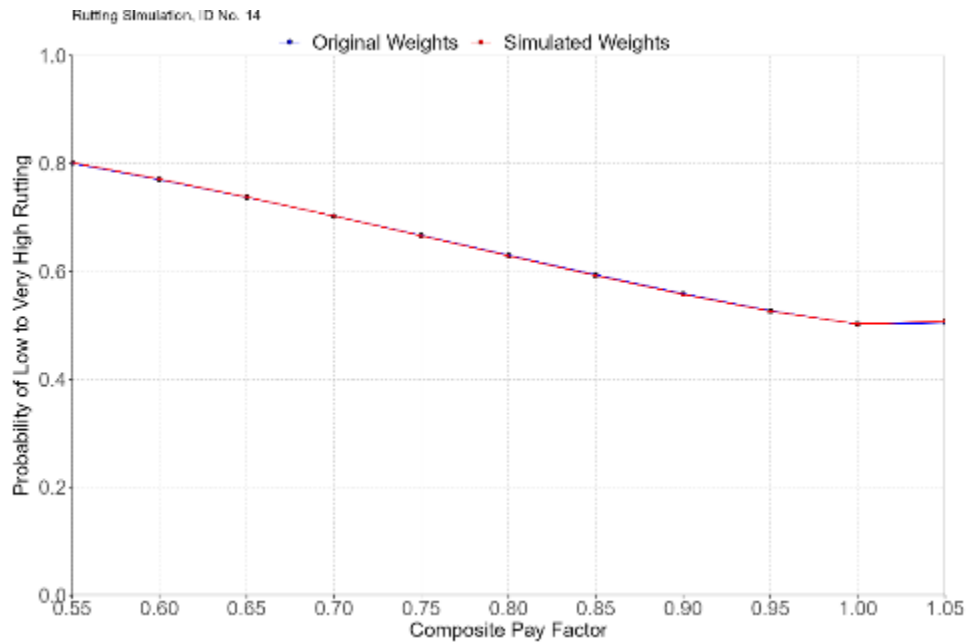


Figure O.14 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 14)

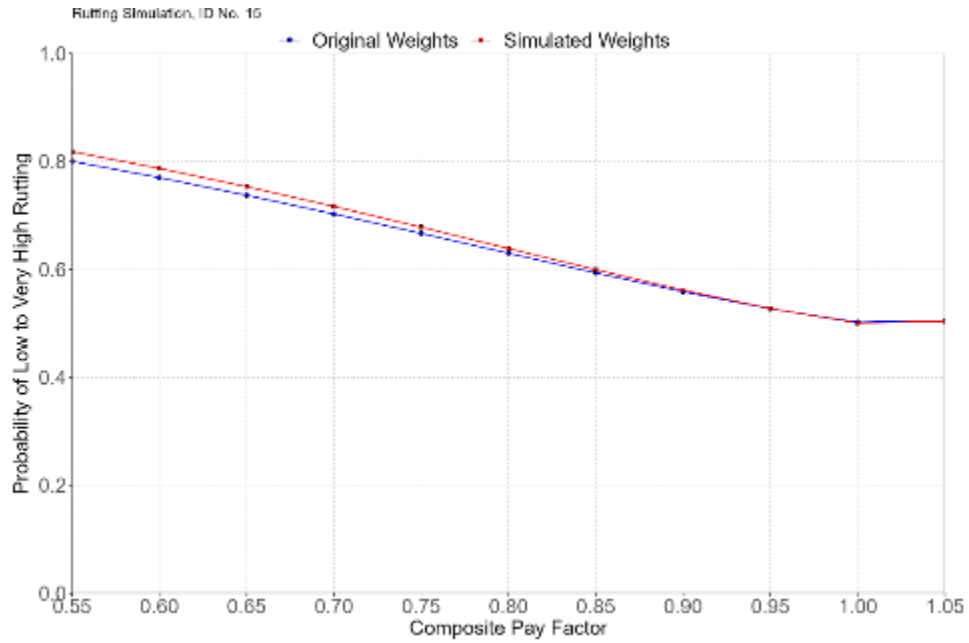


Figure O.15 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 15)

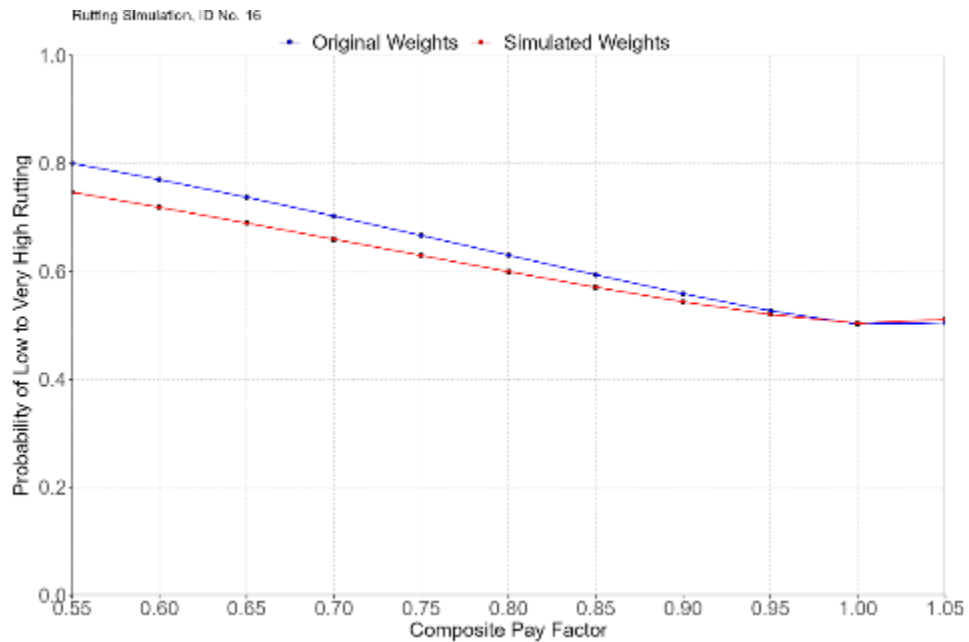


Figure O.16 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 16)

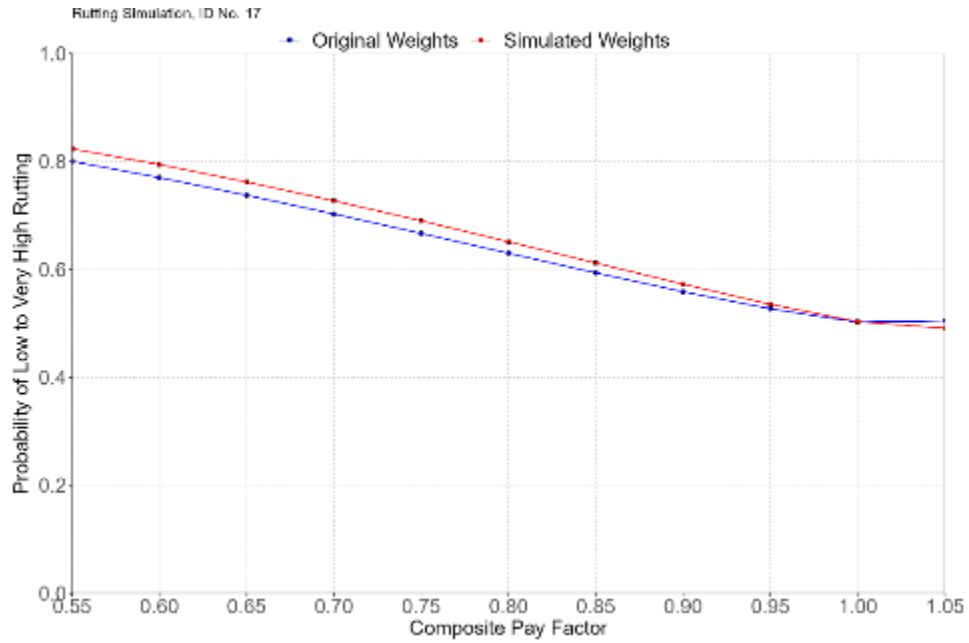


Figure O.17 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 17)

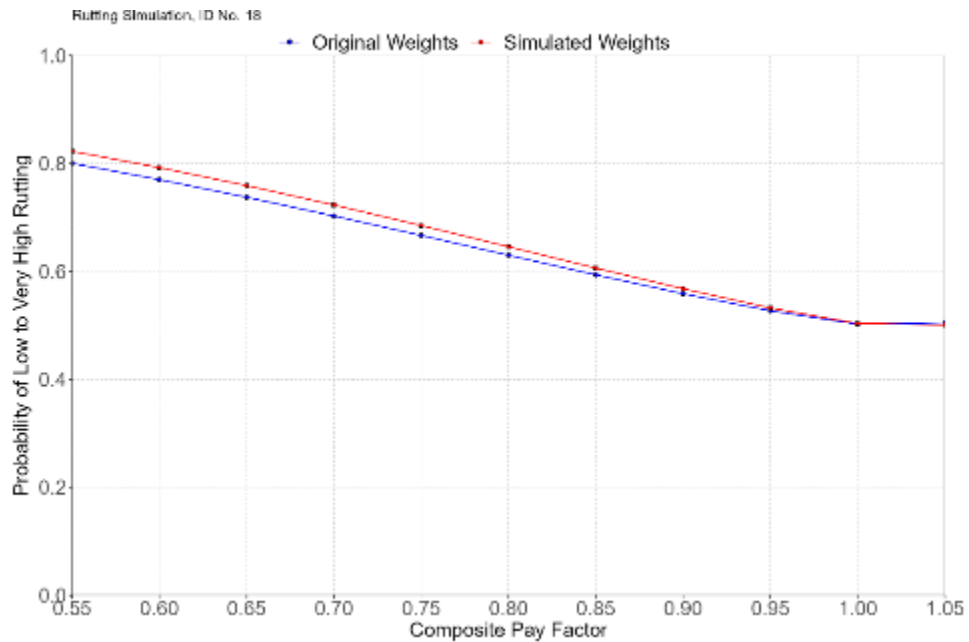


Figure O.18 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 18)

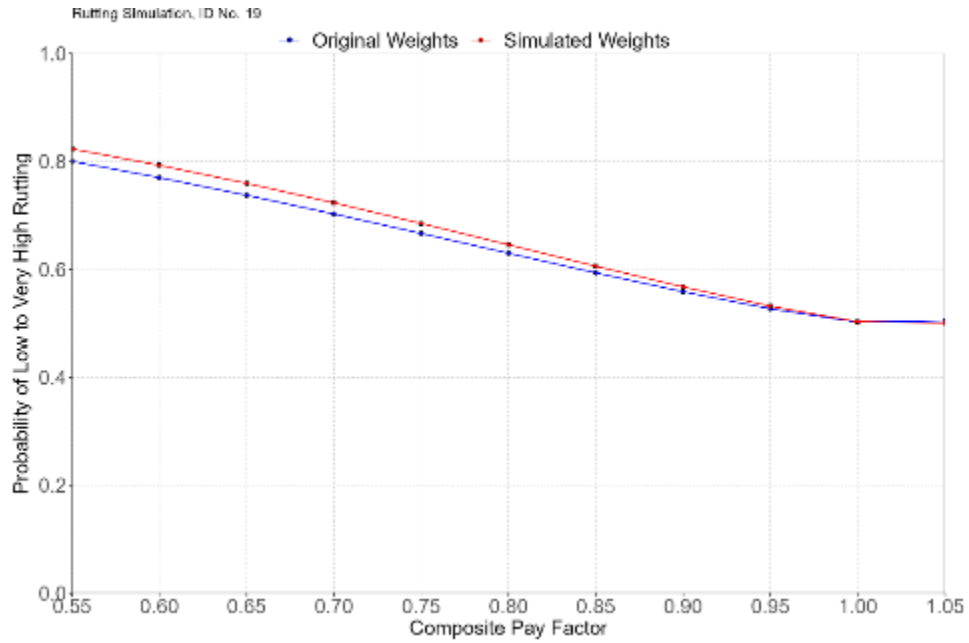


Figure O.19 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 19)

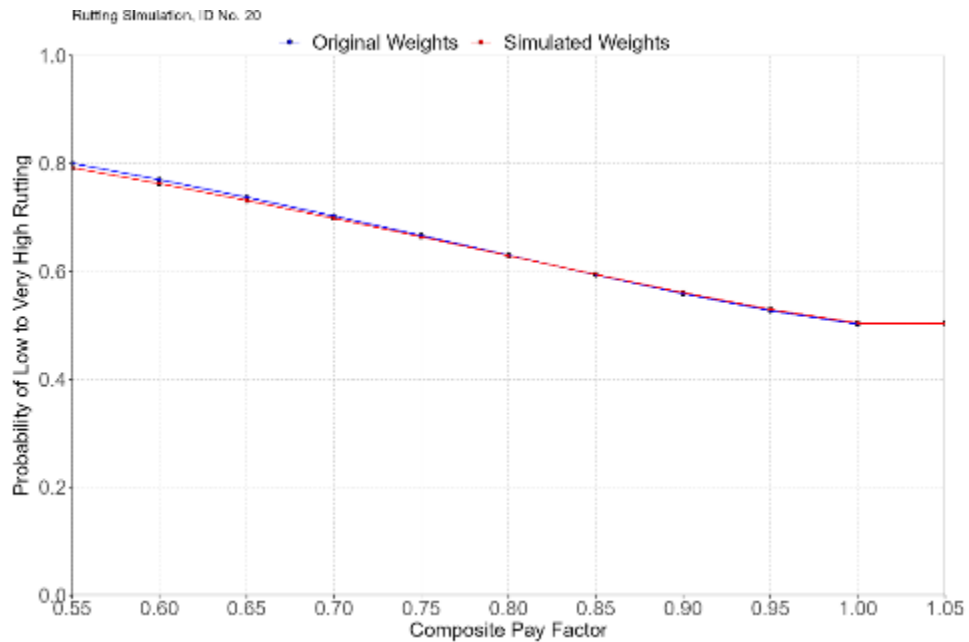


Figure O.20 Rutting Probability Curves for Dense Graded Mixtures (Simulation ID 20)

**APPENDIX P: SIMULATED PROBABILITY CURVES FOR
RAVELING OF DENSE GRADED MIXTURES**

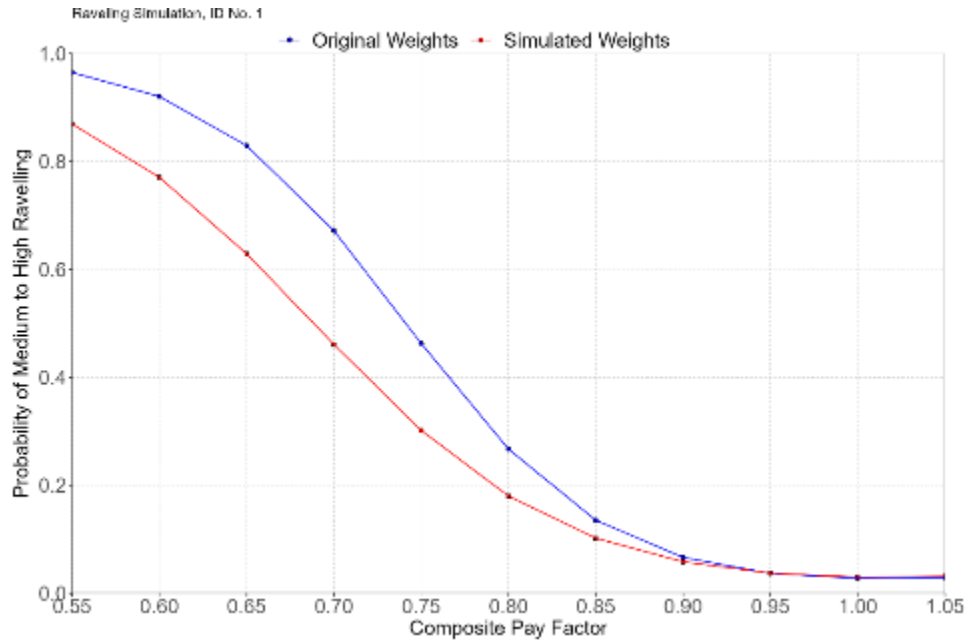


Figure P.1 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 1)

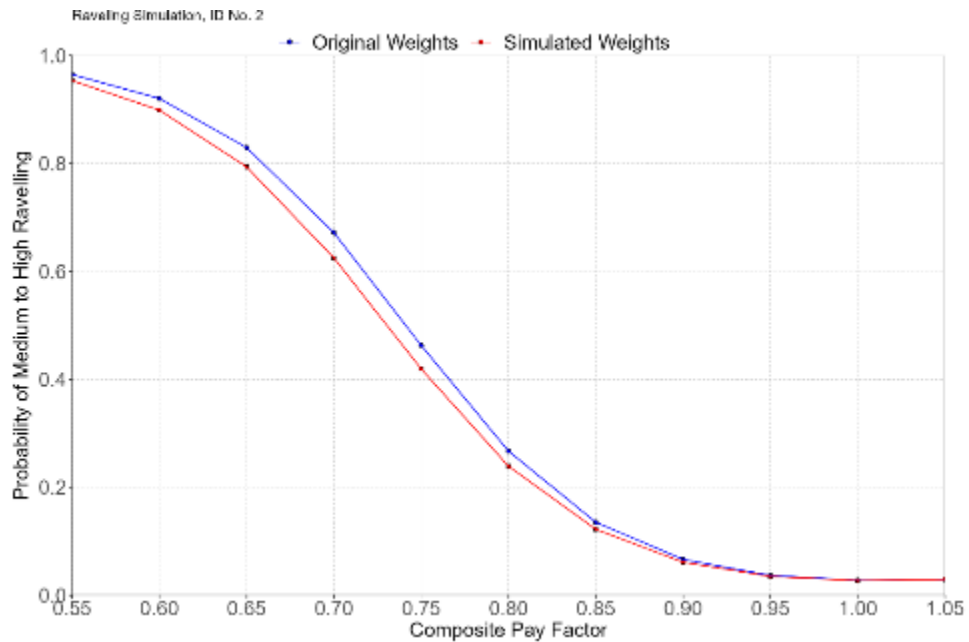


Figure P.2 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 2)

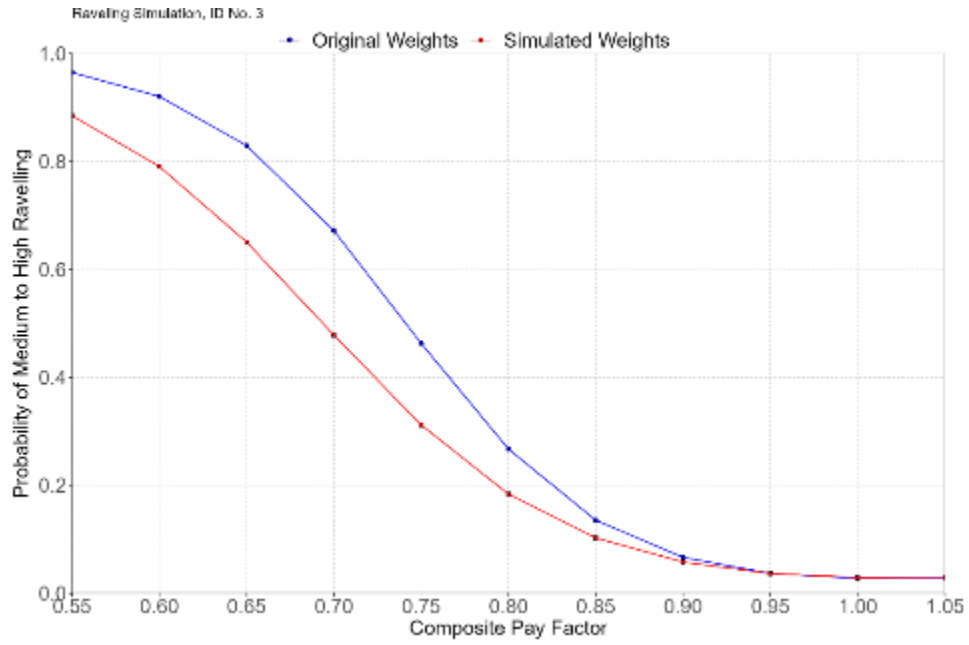


Figure P.3 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 3)

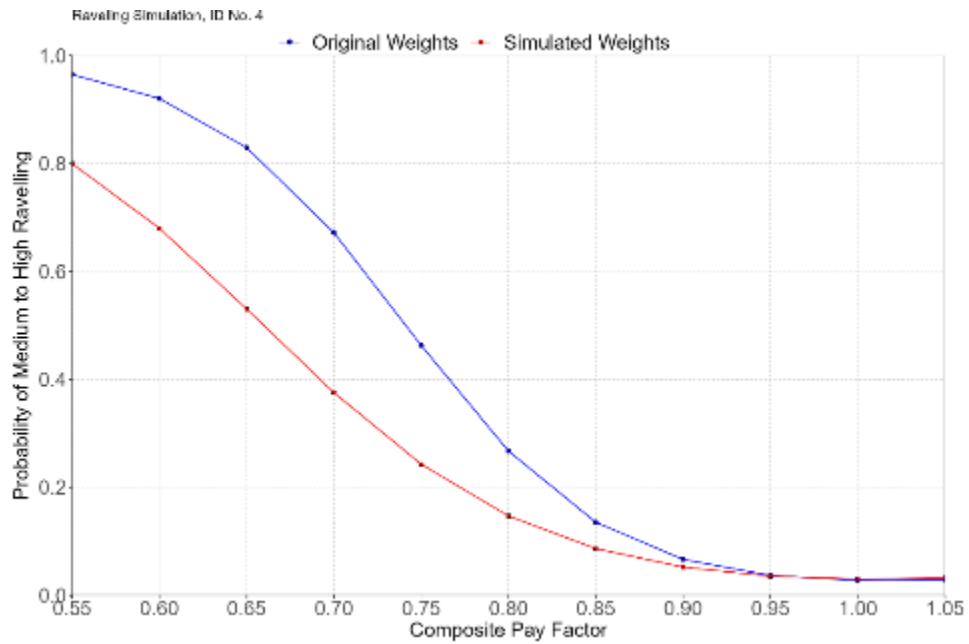


Figure P.4 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 4)

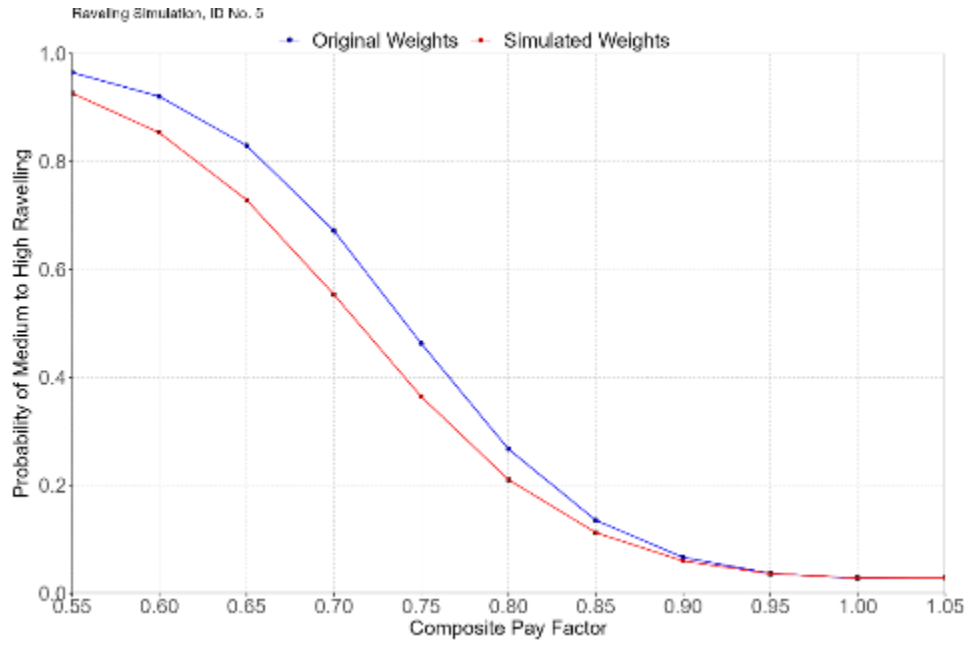


Figure P.5 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 5)

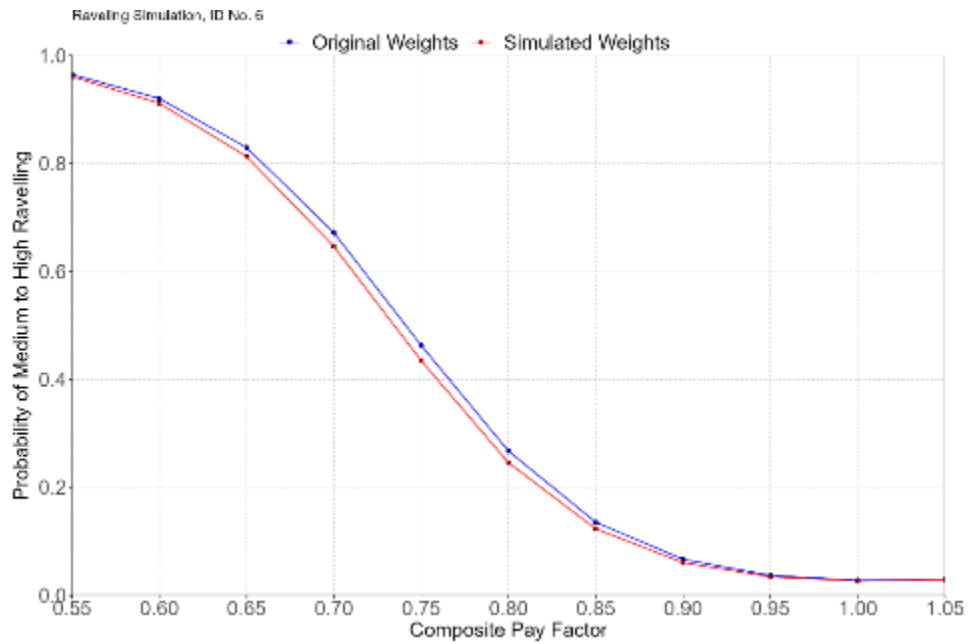


Figure P.6 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 6)

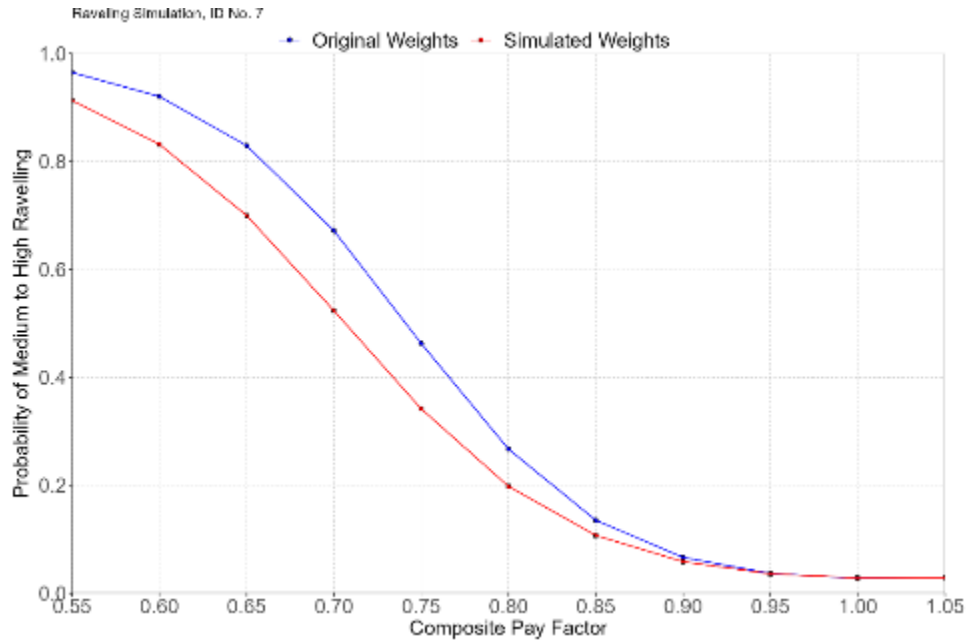


Figure P.7 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 7)

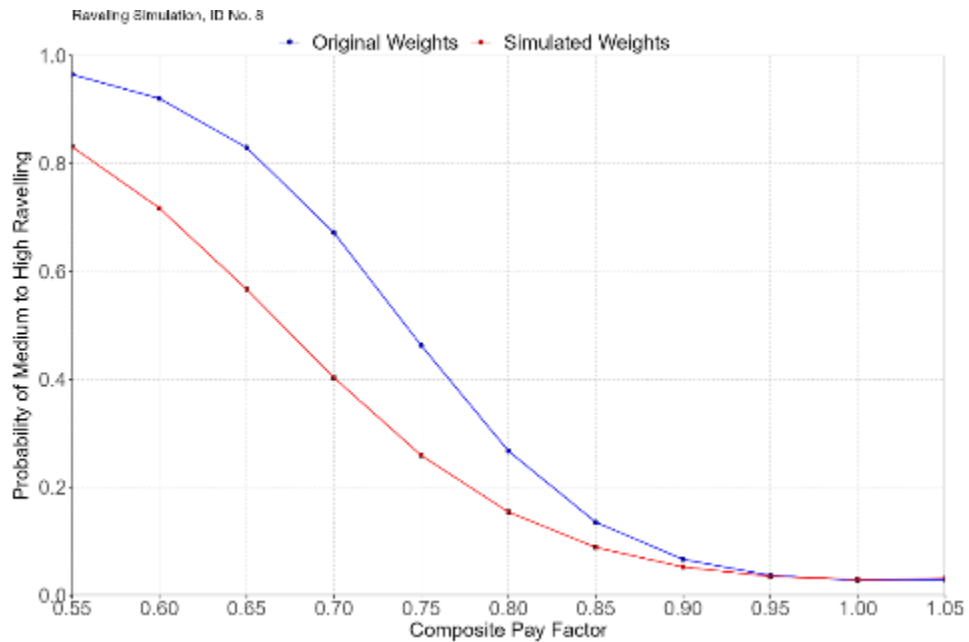


Figure P.8 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 8)

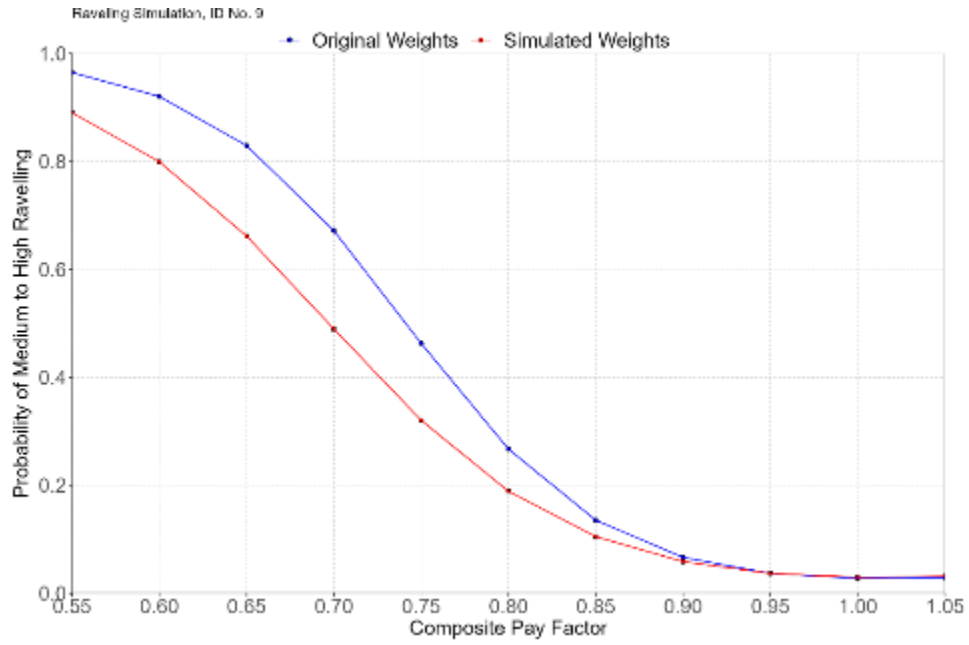


Figure P.9 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 9)

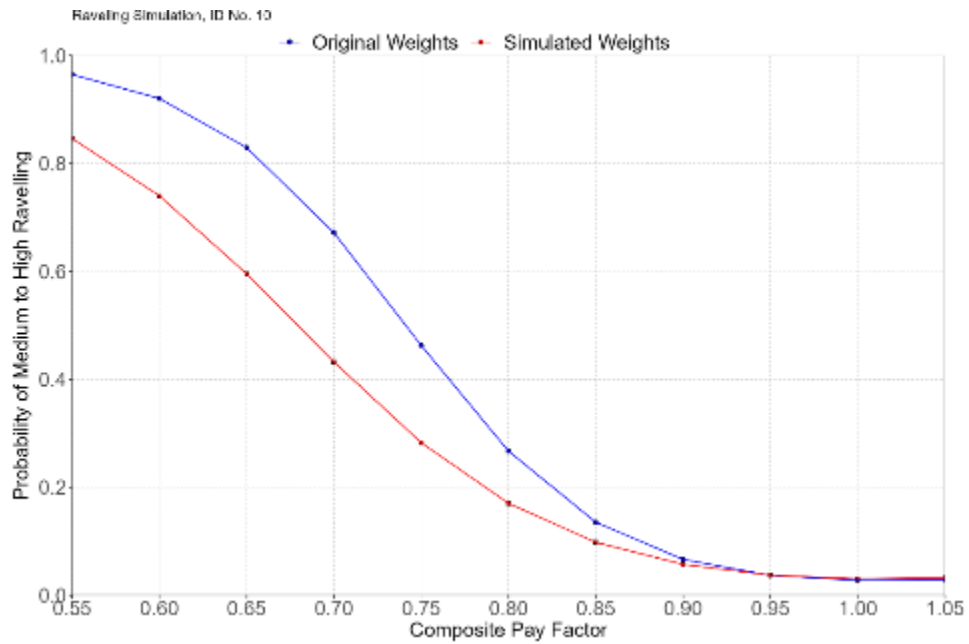


Figure P.10 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 10)

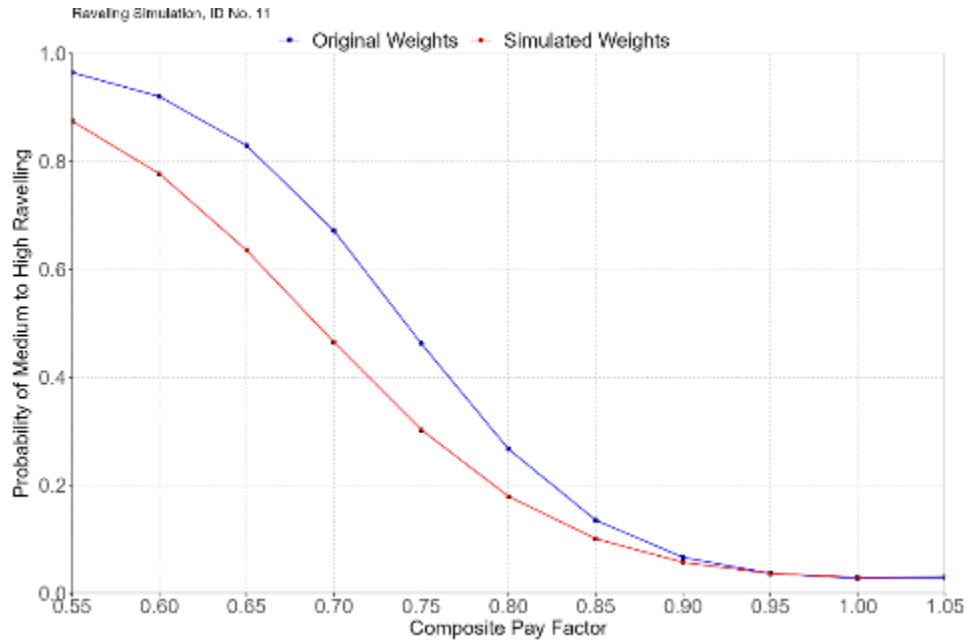


Figure P.11 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 11)

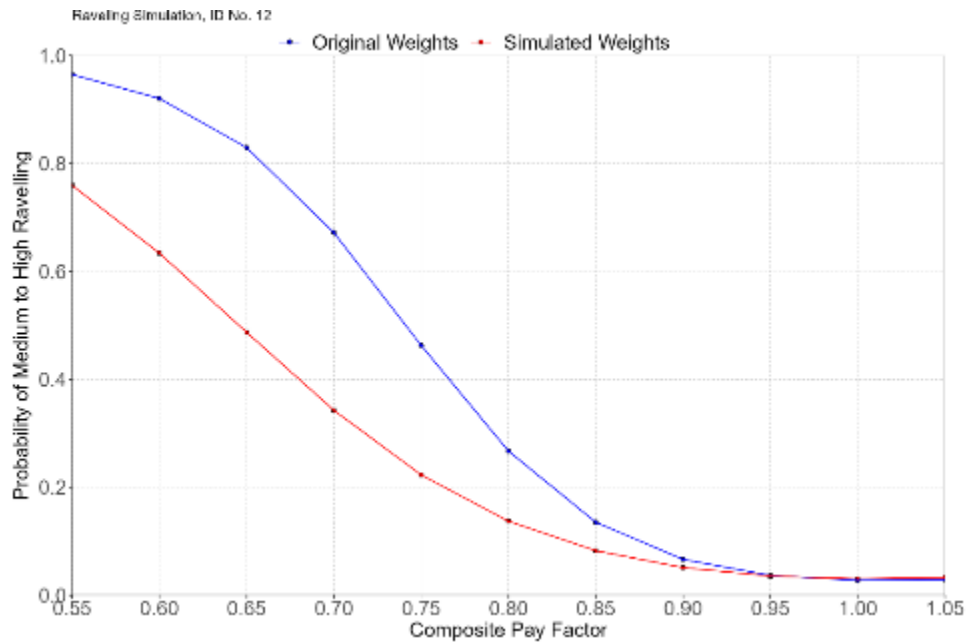


Figure P.12 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 12)

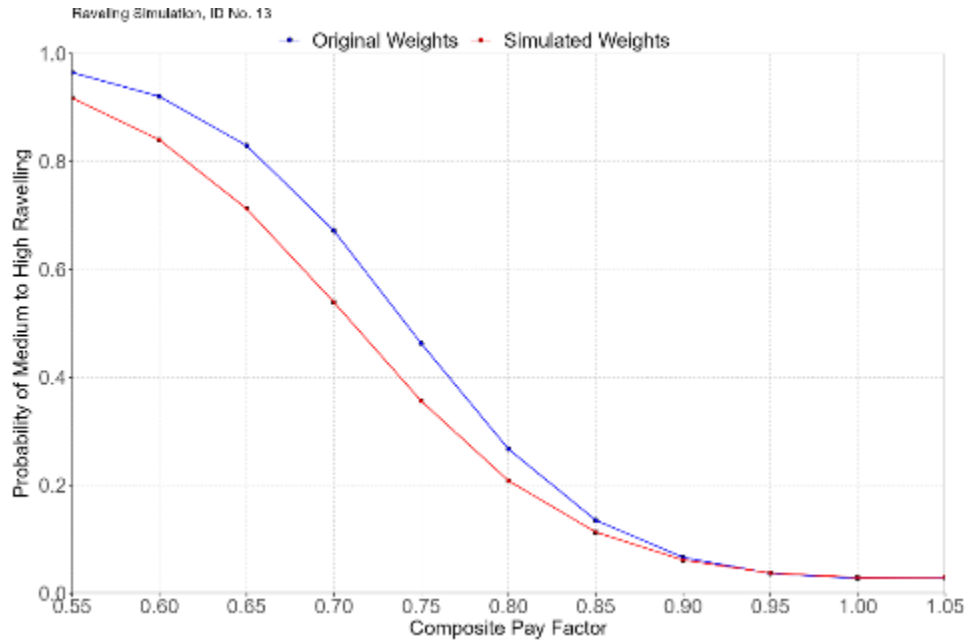


Figure P.13 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 13)

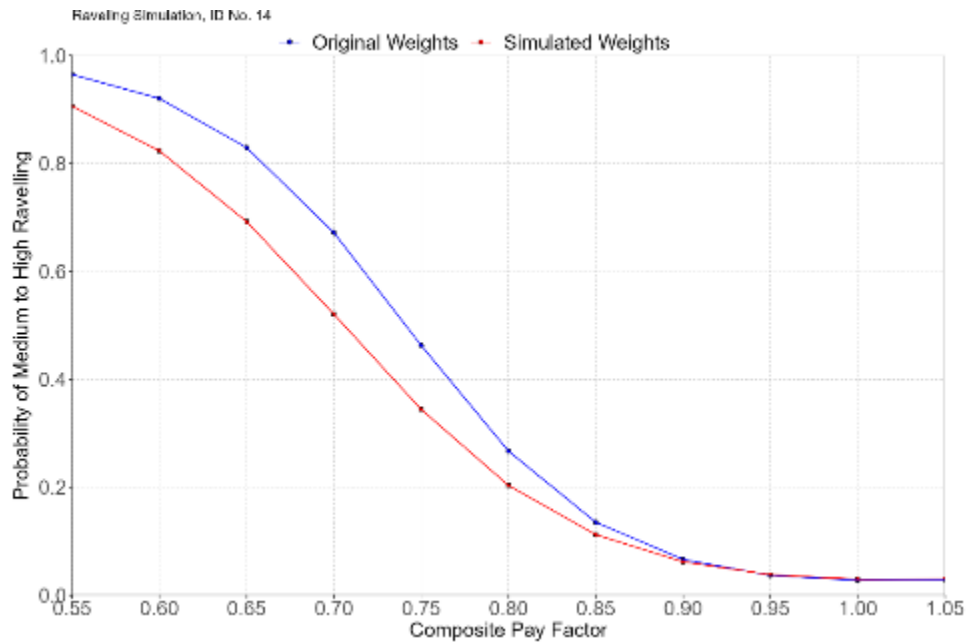


Figure P.14 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 14)

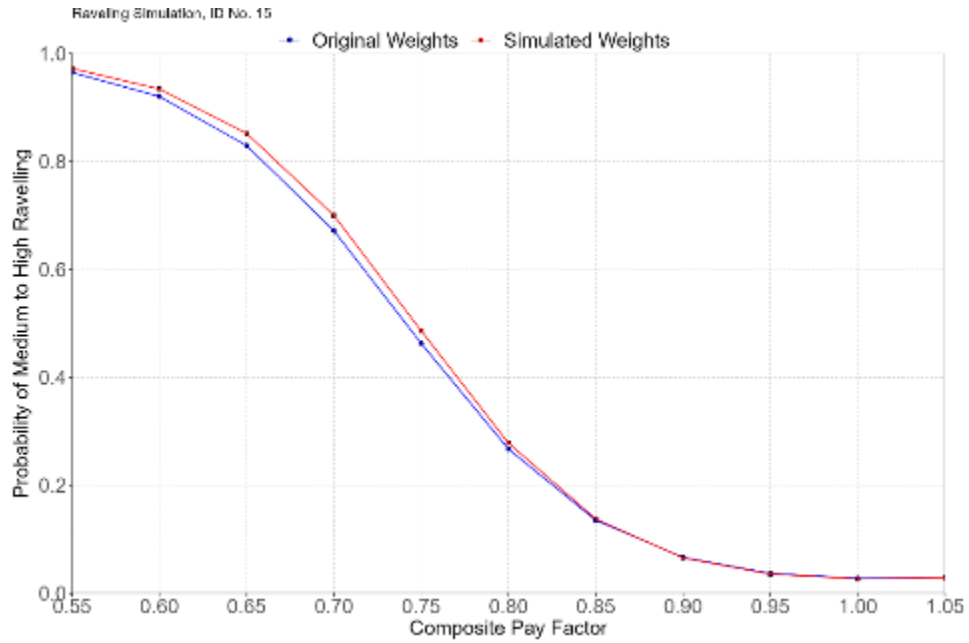


Figure P.15 Raveling Probability Curves for Dense Graded Mixtures (Simulation ID 15)

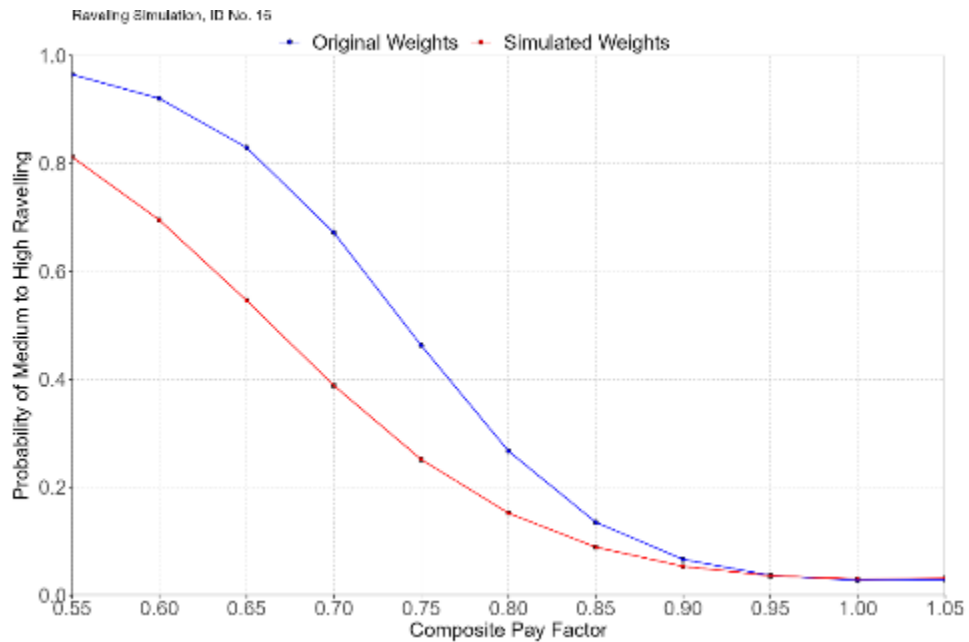


Figure P.16 Raveling Probability Curves for Dense Graded Mixtures (Simulation ID 16)

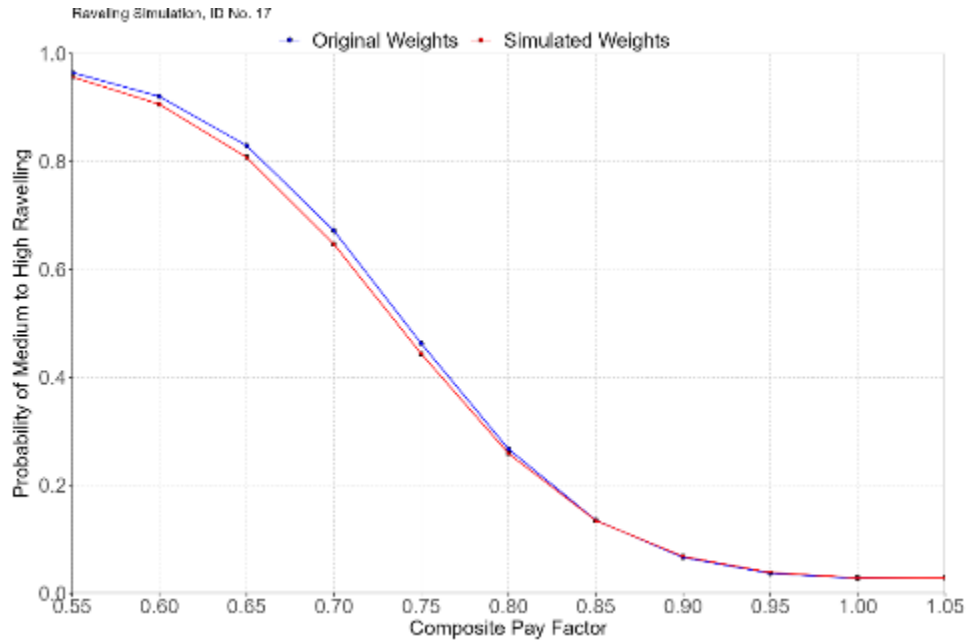


Figure P.17 Raveling Probability Curves for Dense Graded Mixtures (Simulation ID 17)

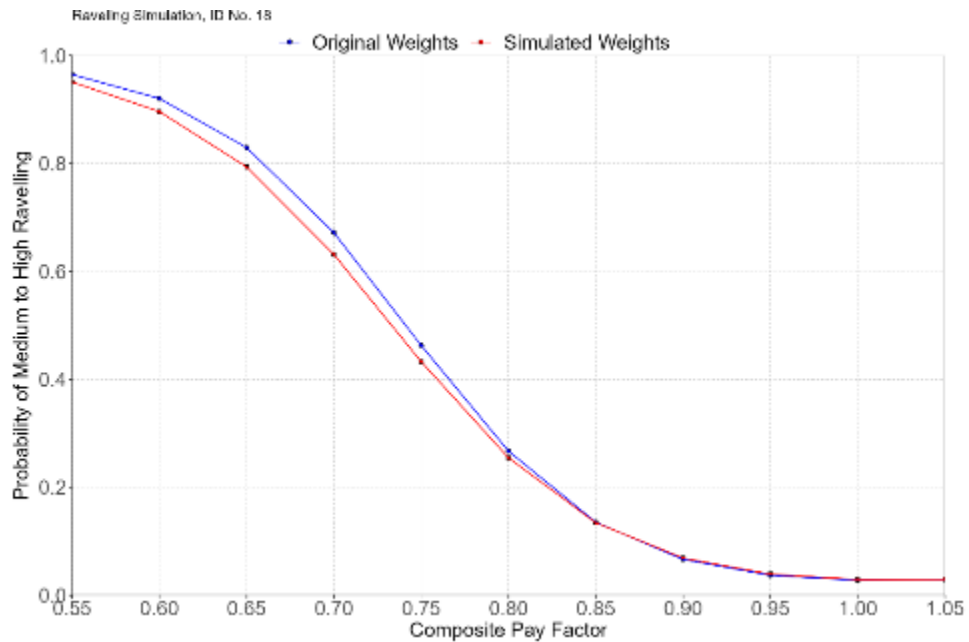


Figure P.18 Raveling Probability Curves for Dense Graded Mixtures (Simulation ID 18)

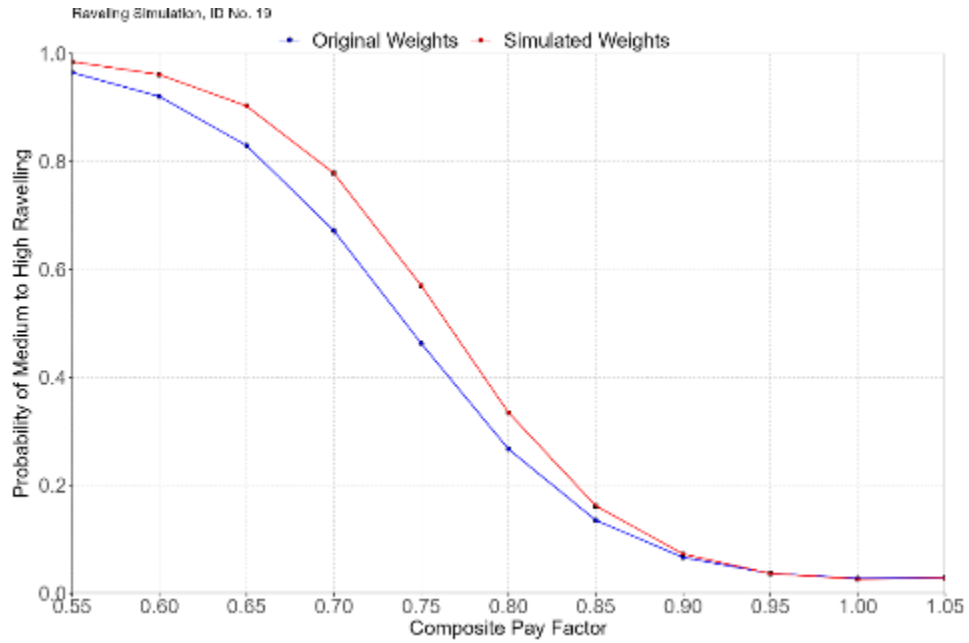


Figure P.19 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 19)

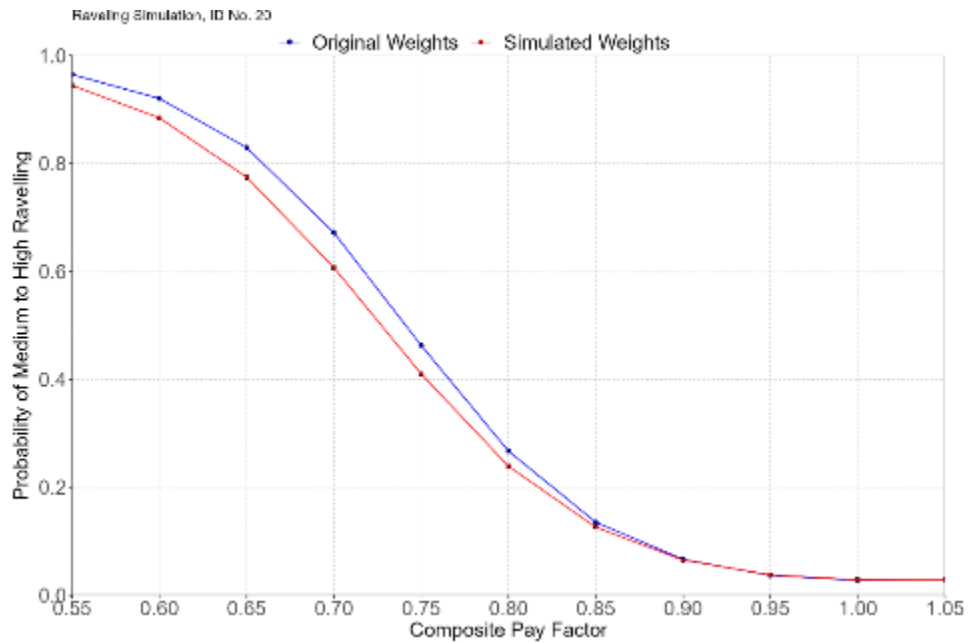


Figure P.20 Ravelling Probability Curves for Dense Graded Mixtures (Simulation ID 20)

**APPENDIX Q: SIMULATED PROBABILITY CURVES FOR
CRACKING OF OPEN GRADED MIXTURES**

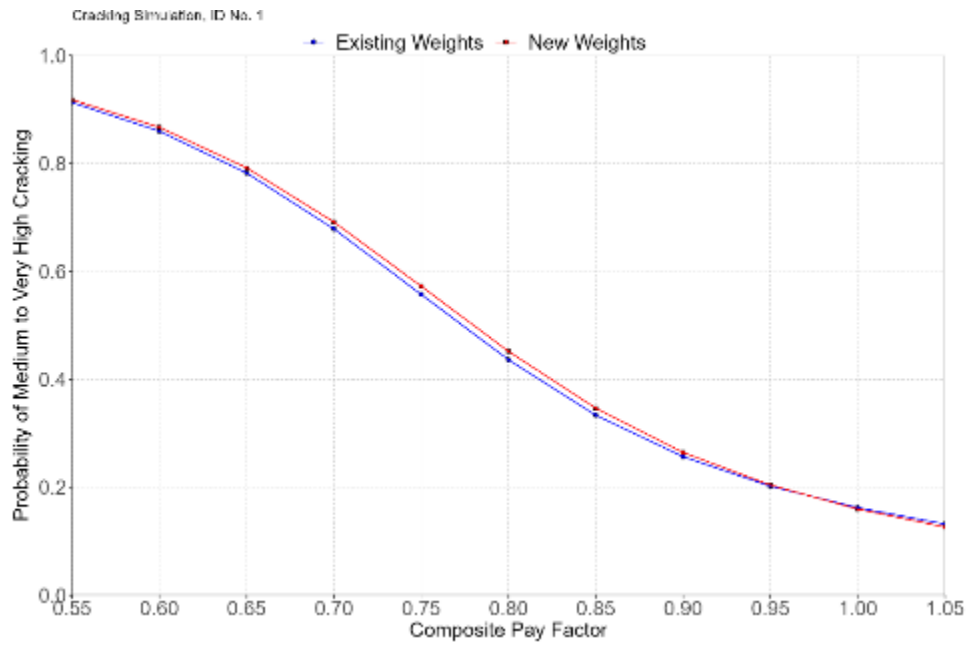


Figure Q.1 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 1)

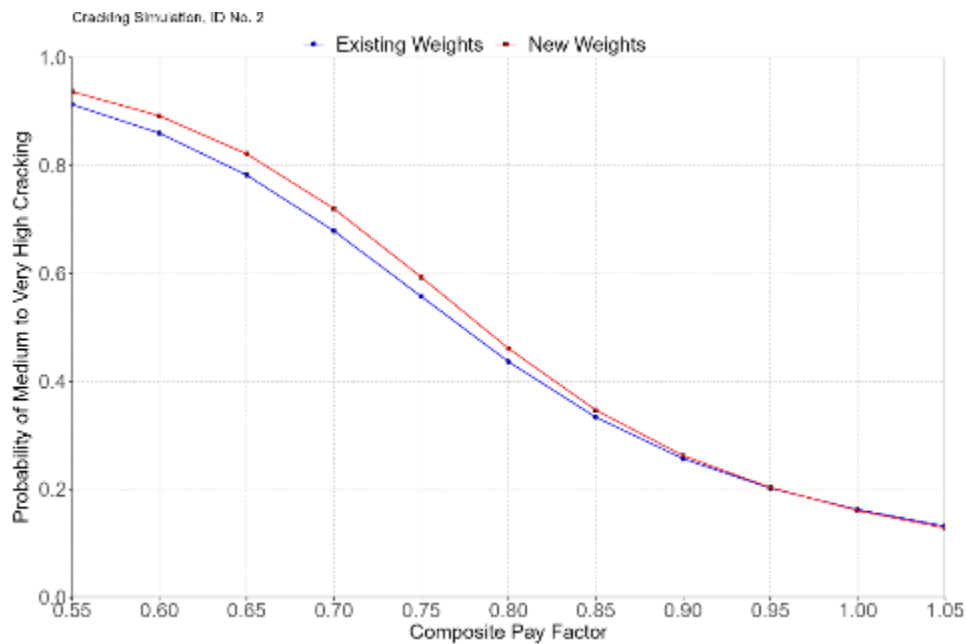


Figure Q.2 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 2)

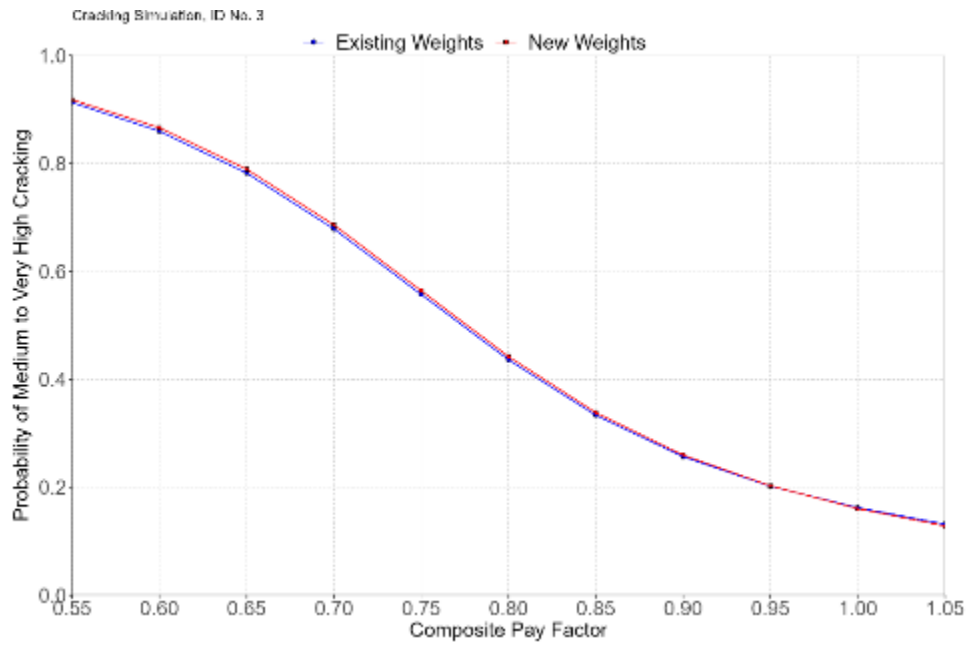


Figure Q.3 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 3)

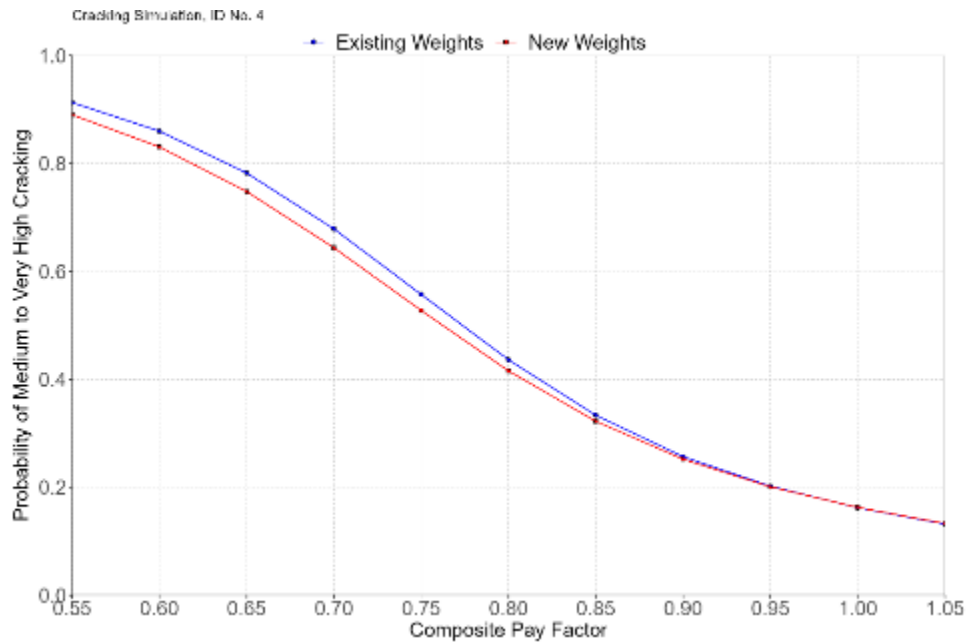


Figure Q.4 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 4)

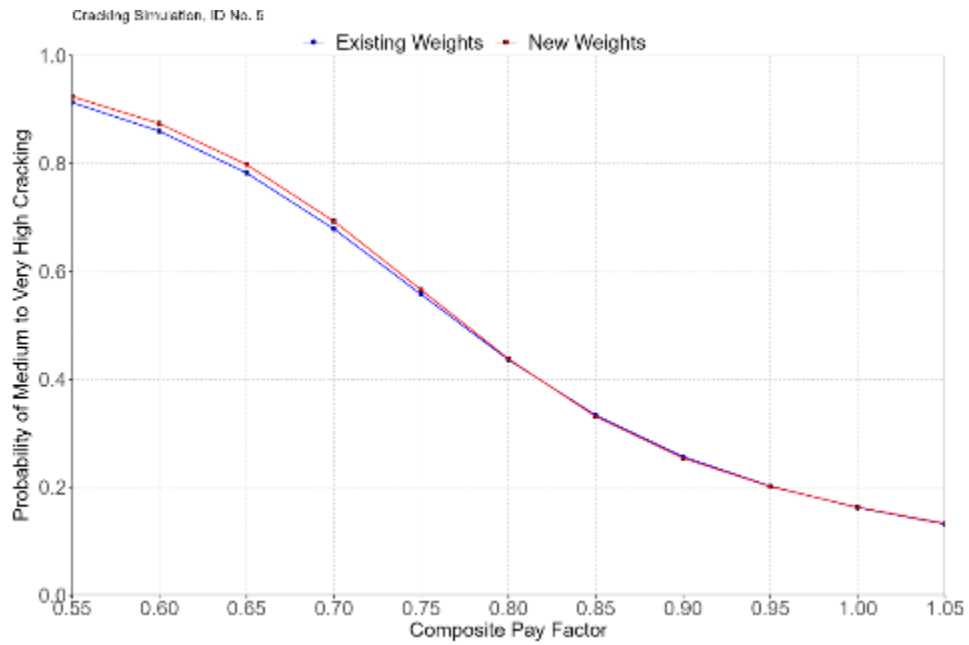


Figure Q.5 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 5)

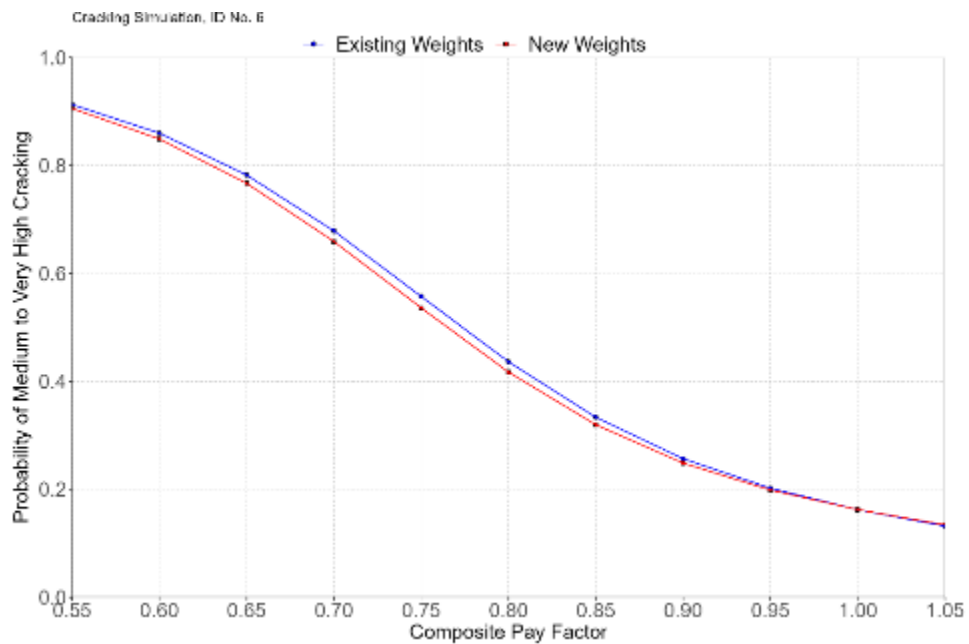


Figure Q.6 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 6)

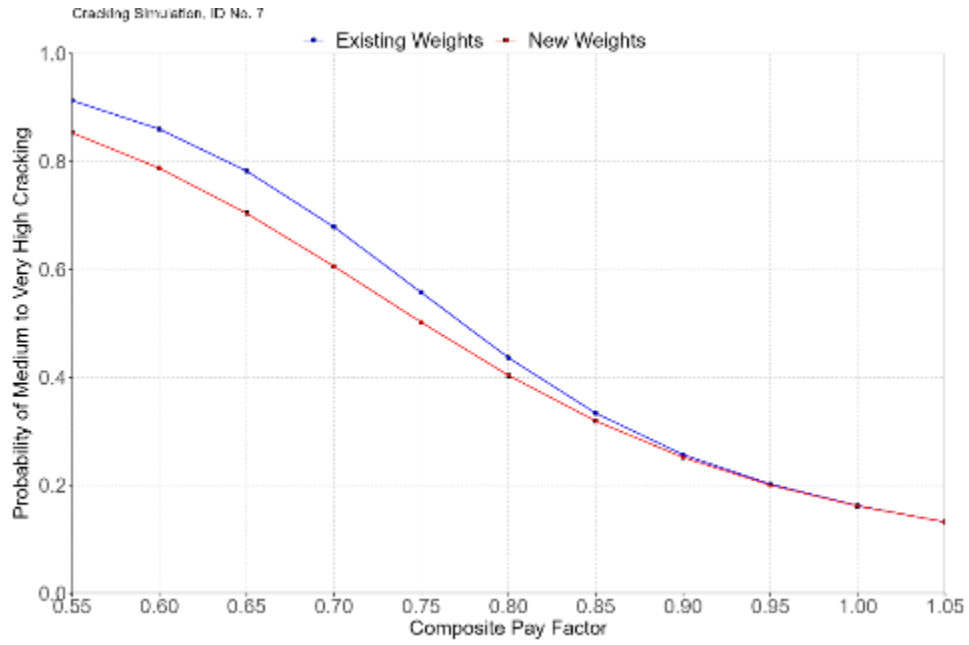


Figure Q.7 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 7)

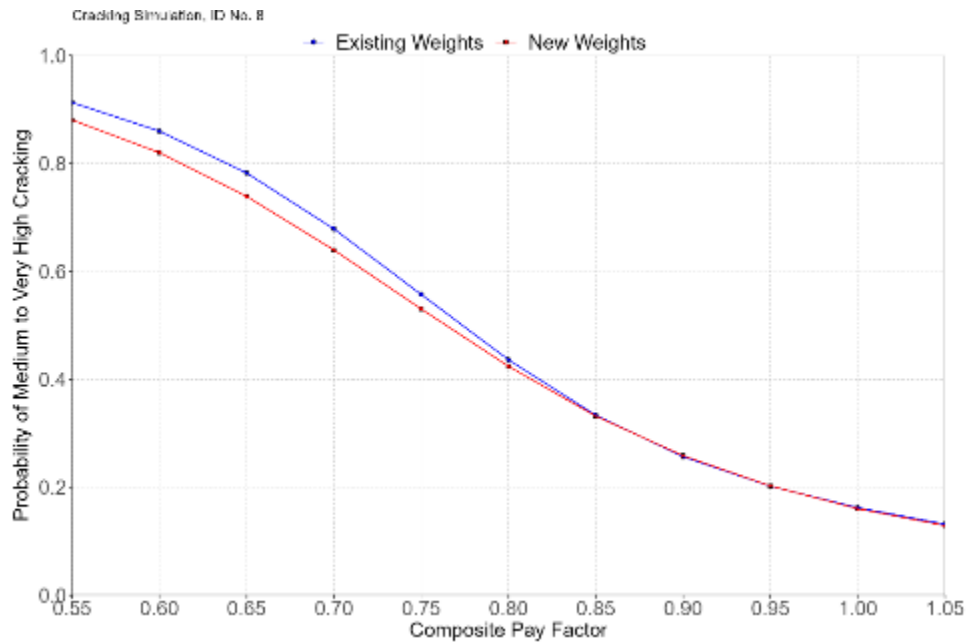


Figure Q.8 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 8)

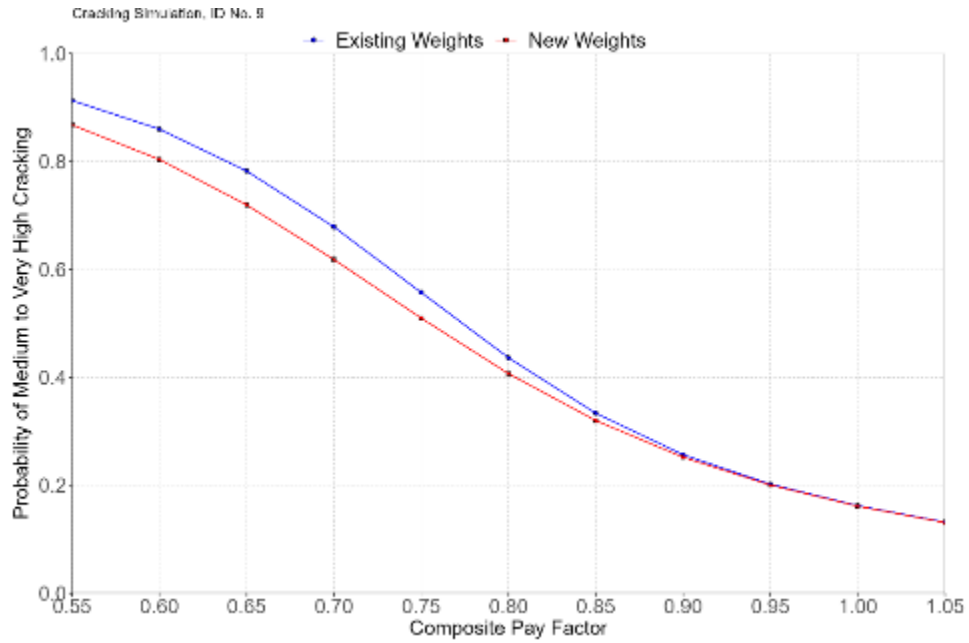


Figure Q.9 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 9)

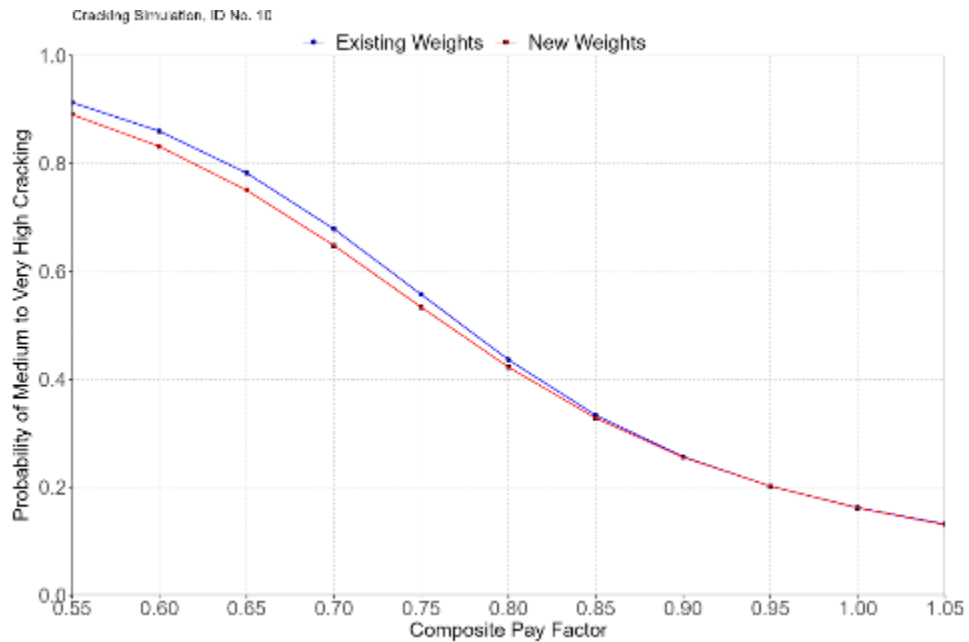


Figure Q.10 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 10)

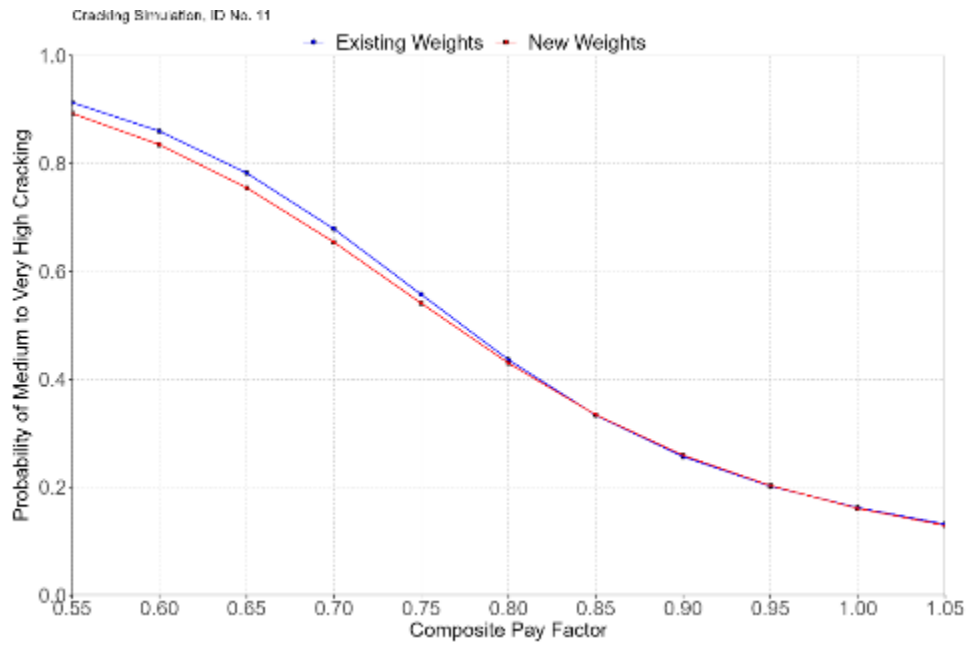


Figure Q.11 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 11)

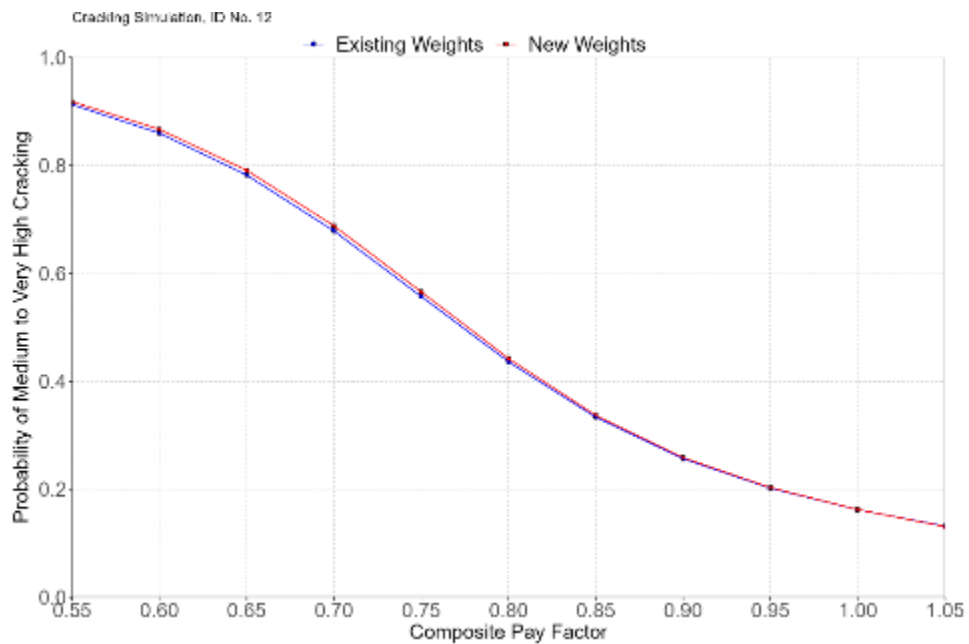


Figure Q.12 Cracking Probability Curves for Open Graded Mixtures (Simulation ID 12)

**APPENDIX R: SIMULATED PROBABILITY CURVES FOR
RUTTING OF OPEN GRADED MIXTURES**

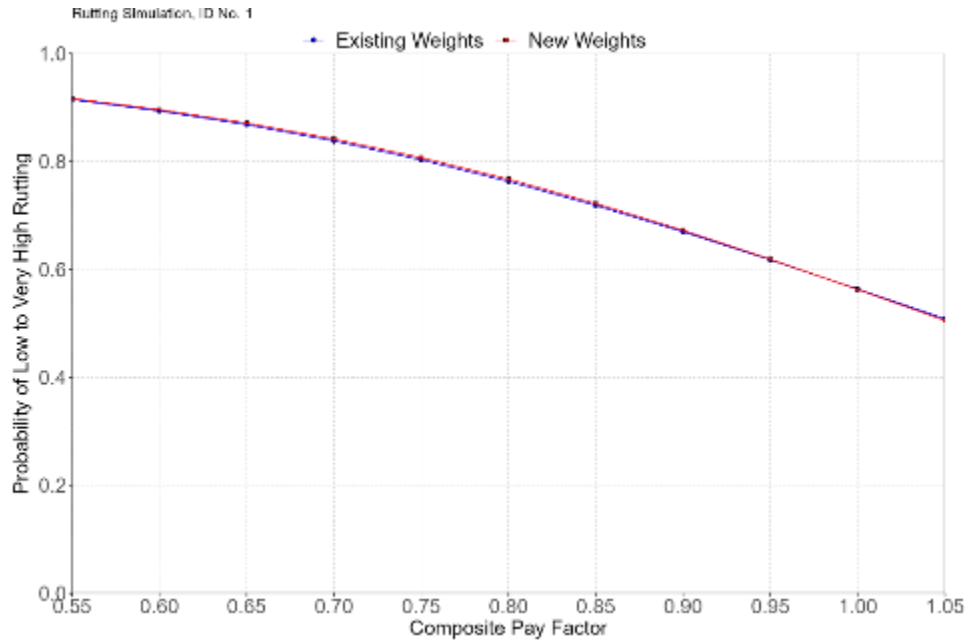


Figure R.1 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 1)

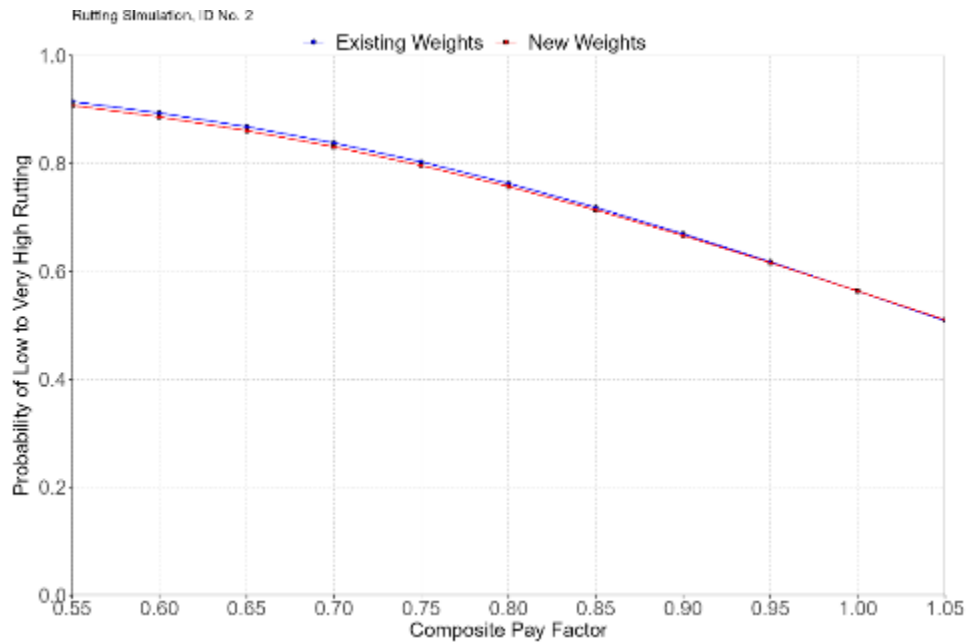


Figure R.2 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 2)

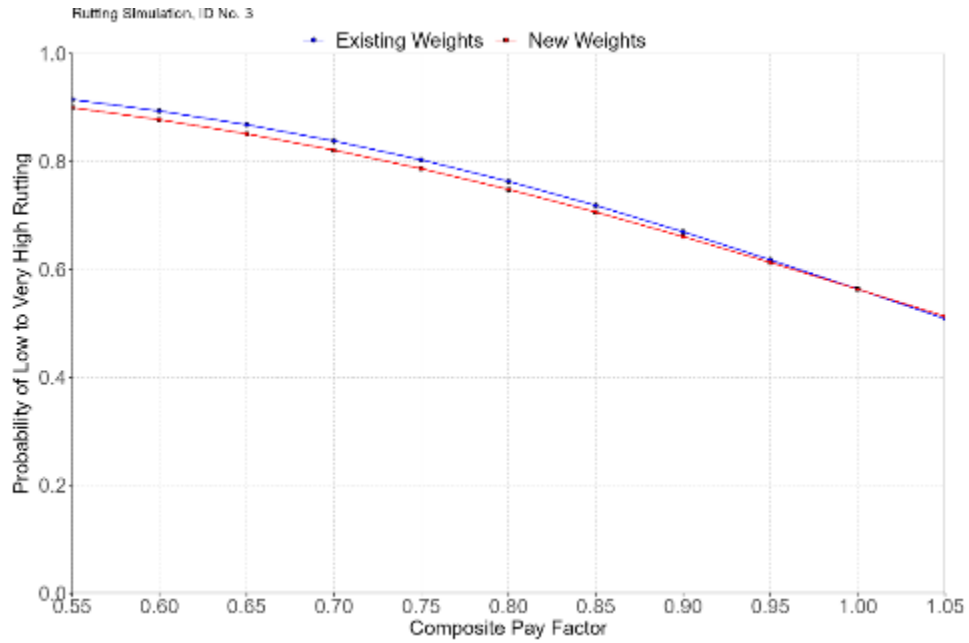


Figure R.3 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 3)

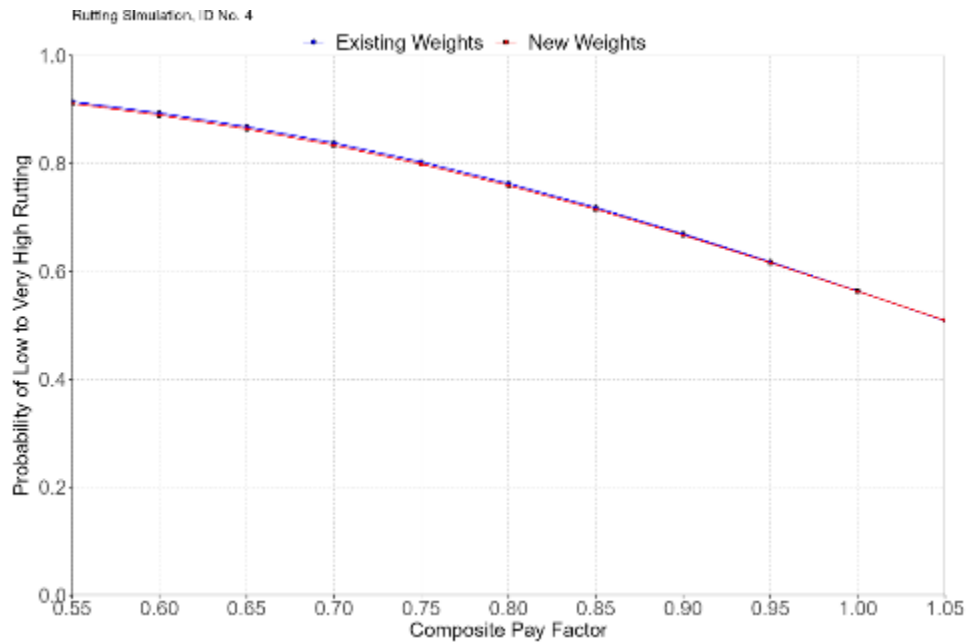


Figure R.4 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 4)

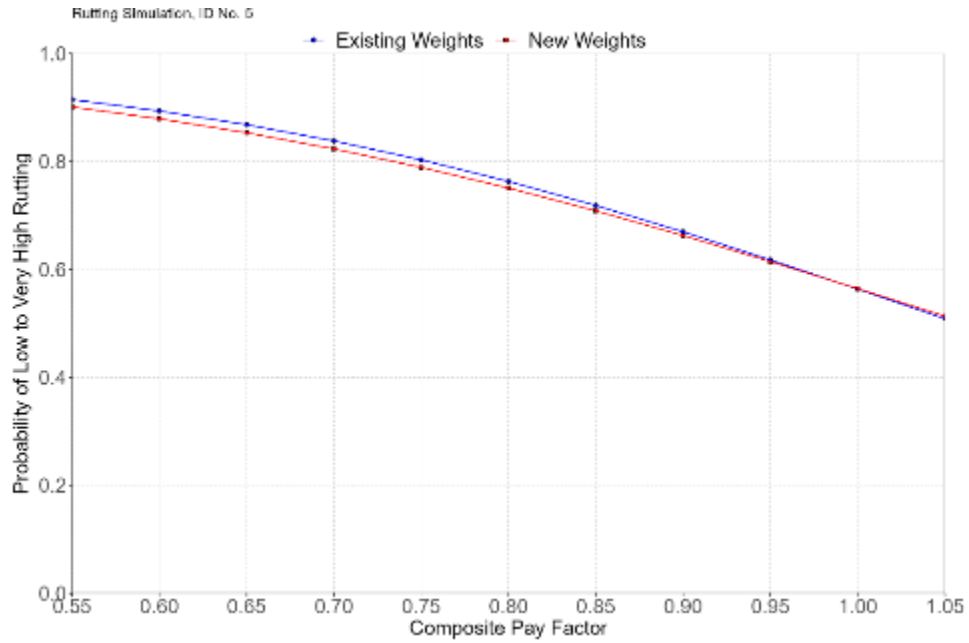


Figure R.5 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 5)

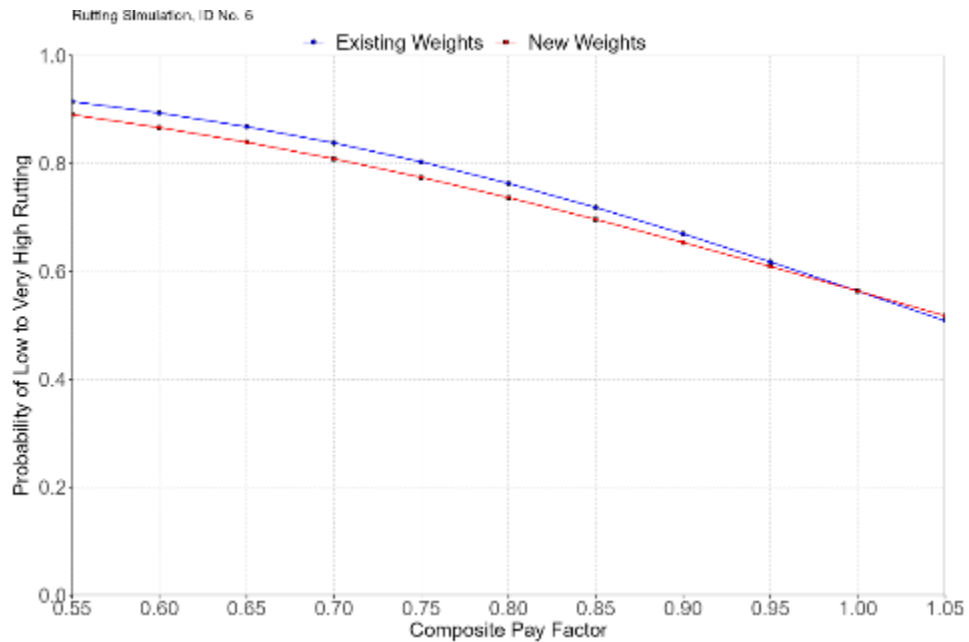


Figure R.6 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 6)

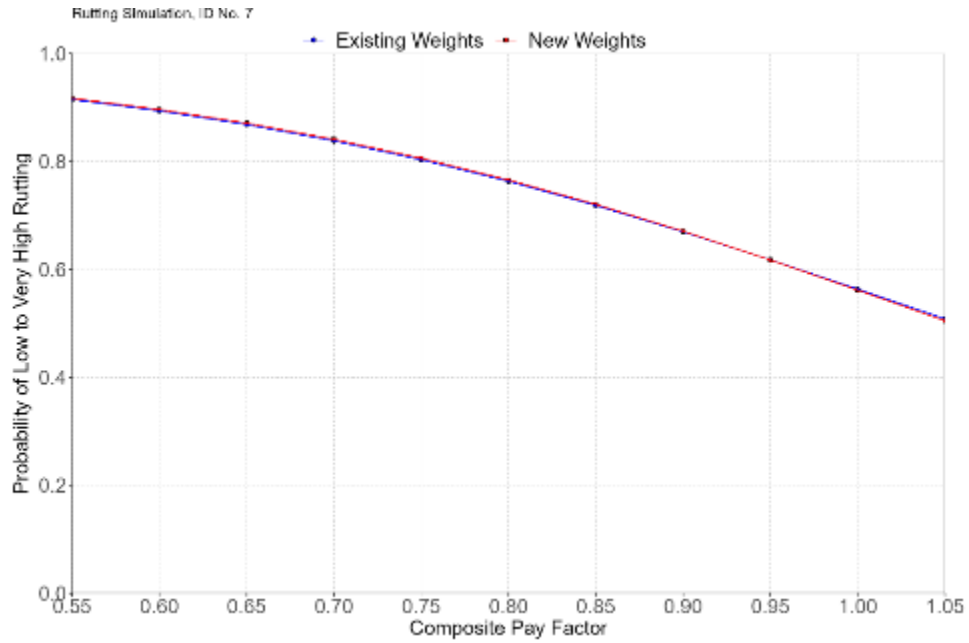


Figure R.7 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 7)

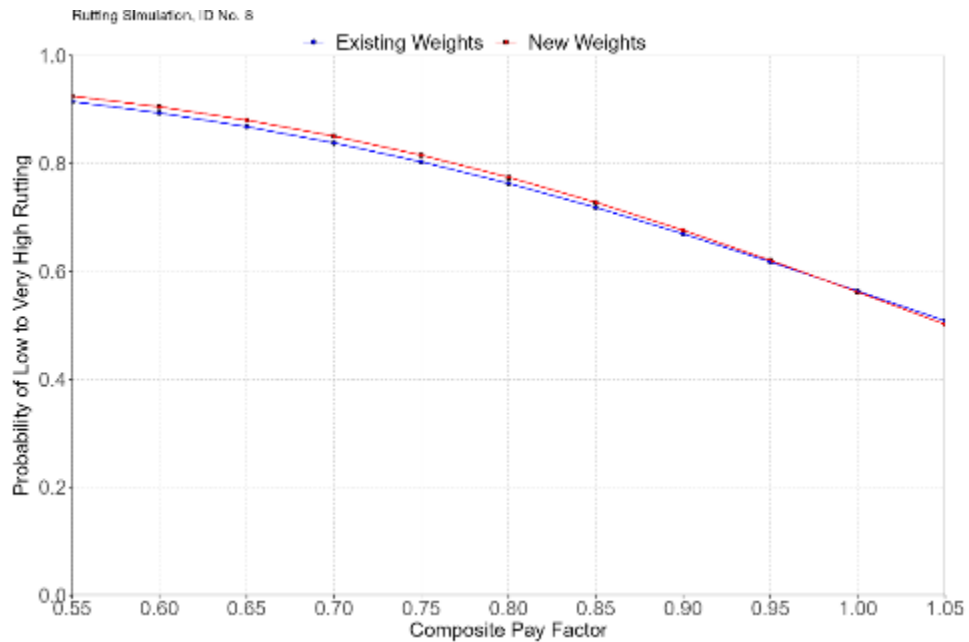


Figure R.8 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 8)

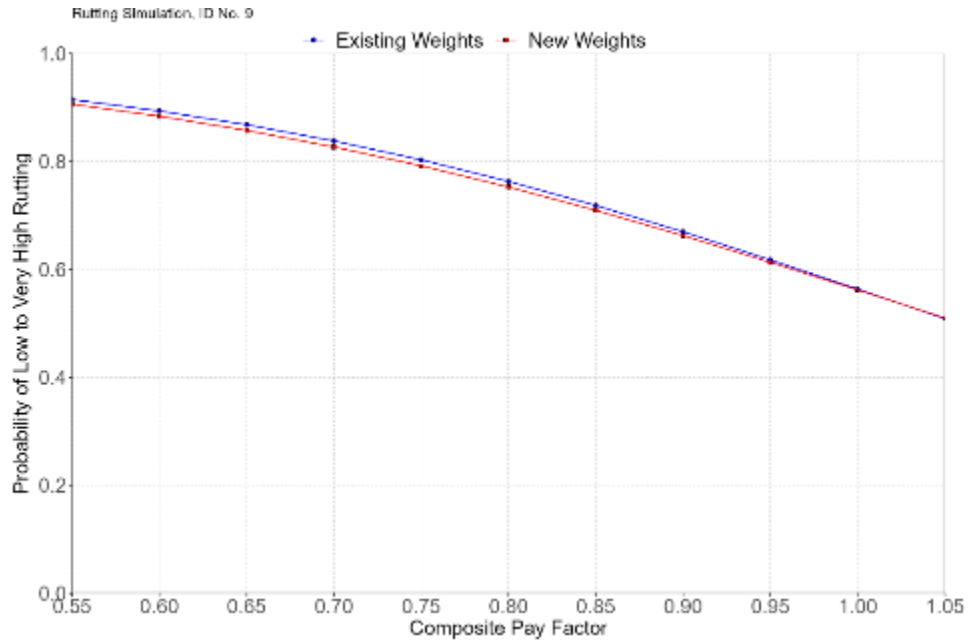


Figure R.9 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 9)

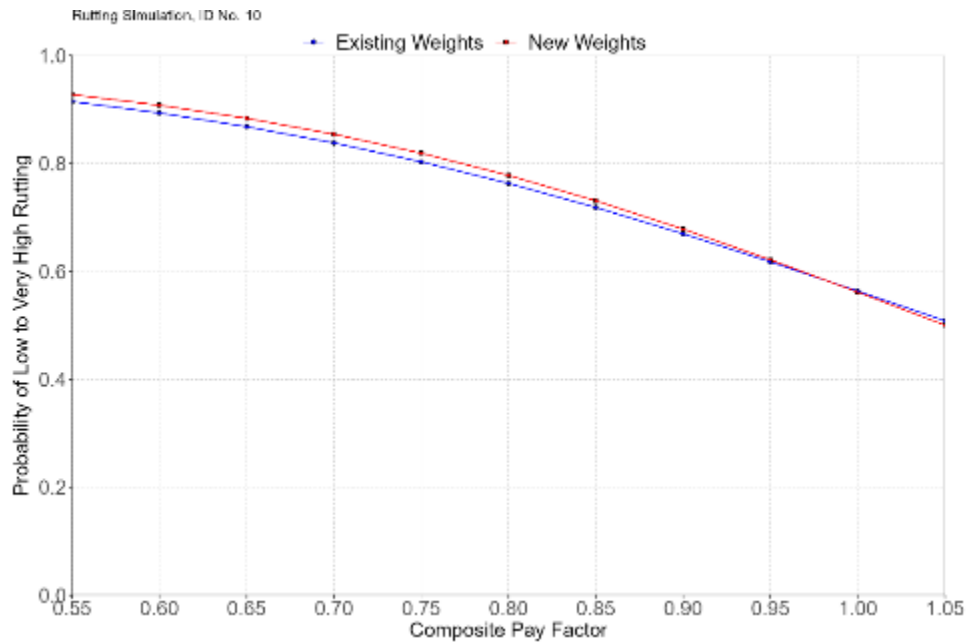


Figure R.10 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 10)

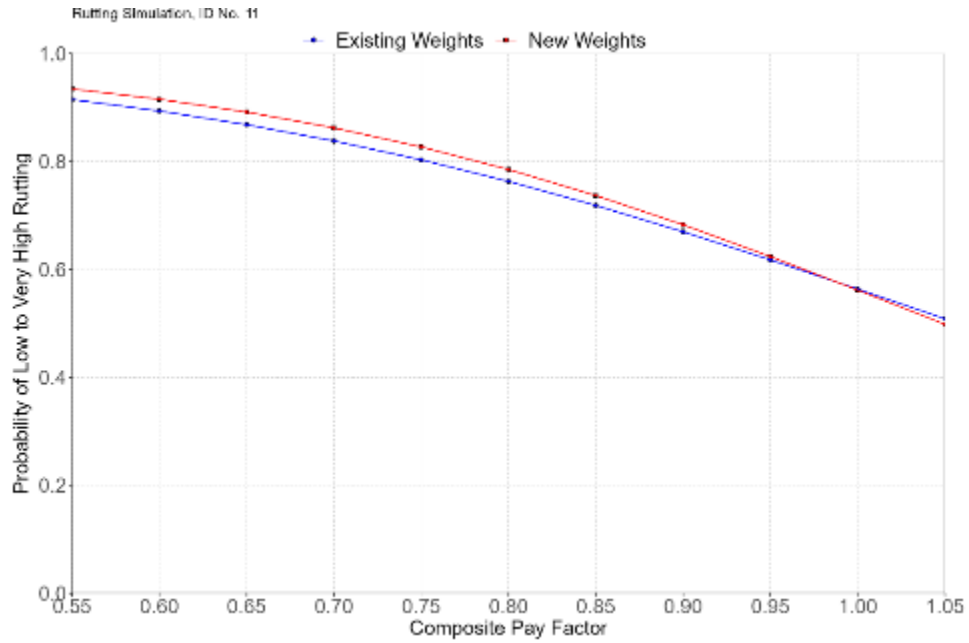


Figure R.11 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 11)

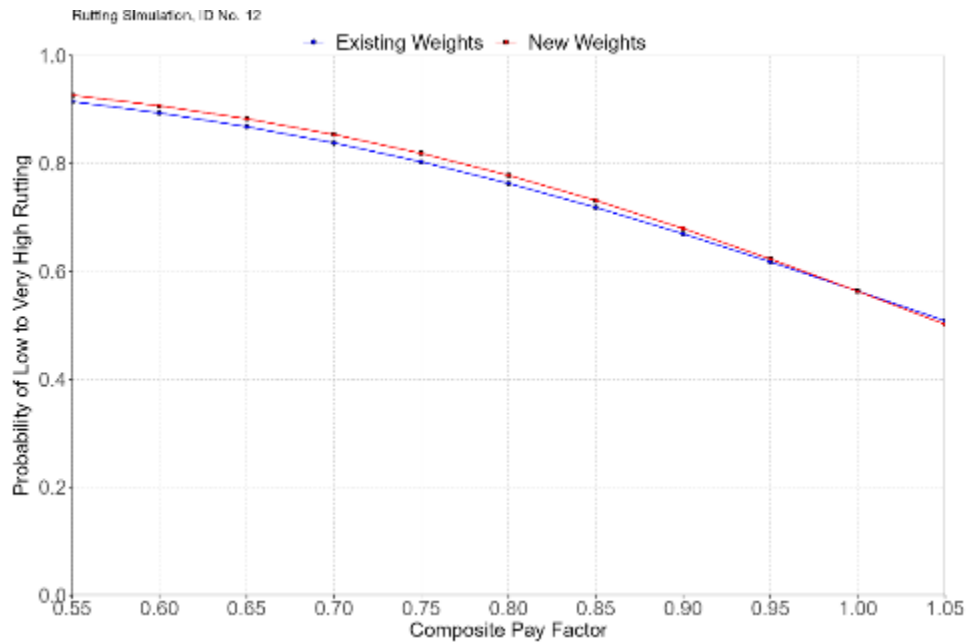


Figure R.12 Rutting Probability Curves for Open Graded Mixtures (Simulation ID 12)

**APPENDIX S: SIMULATED PROBABILITY CURVES FOR
RAVELING OF OPEN GRADED MIXTURES**

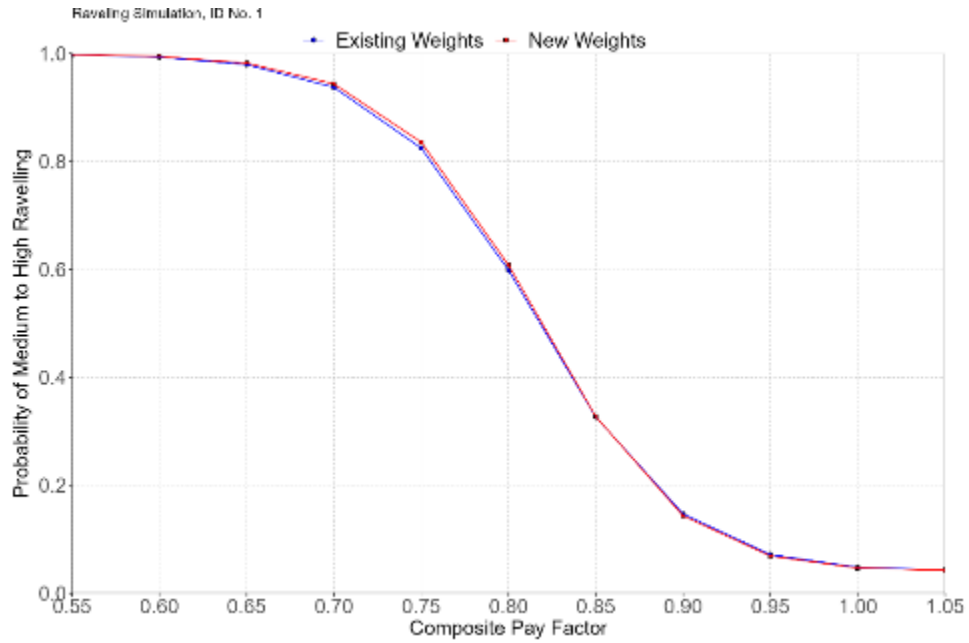


Figure S.1 Raveling Probability Curves for Open Graded Mixtures (Simulation ID 1)

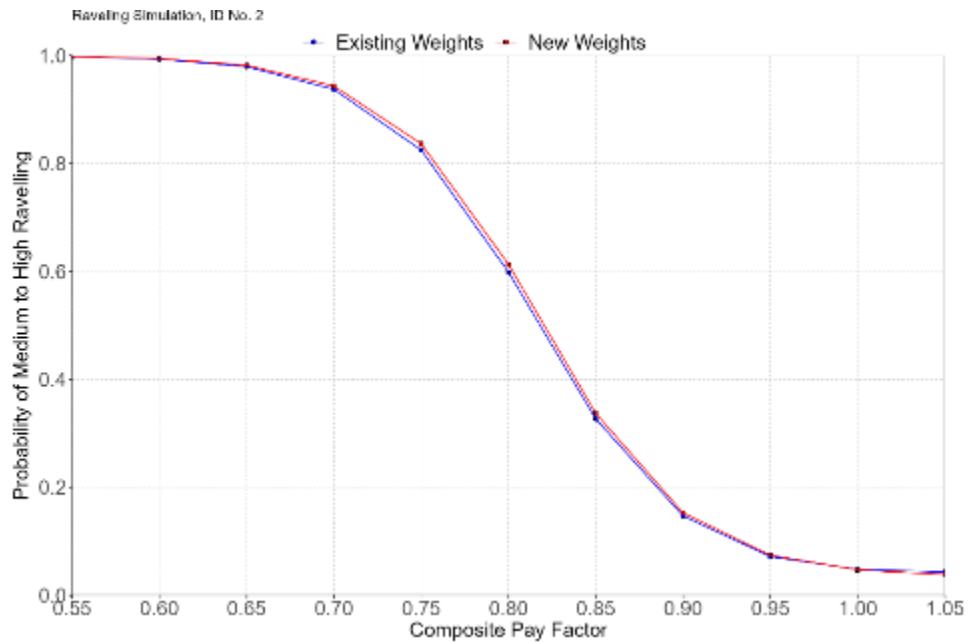


Figure S.2 Raveling Probability Curves for Open Graded Mixtures (Simulation ID 2)

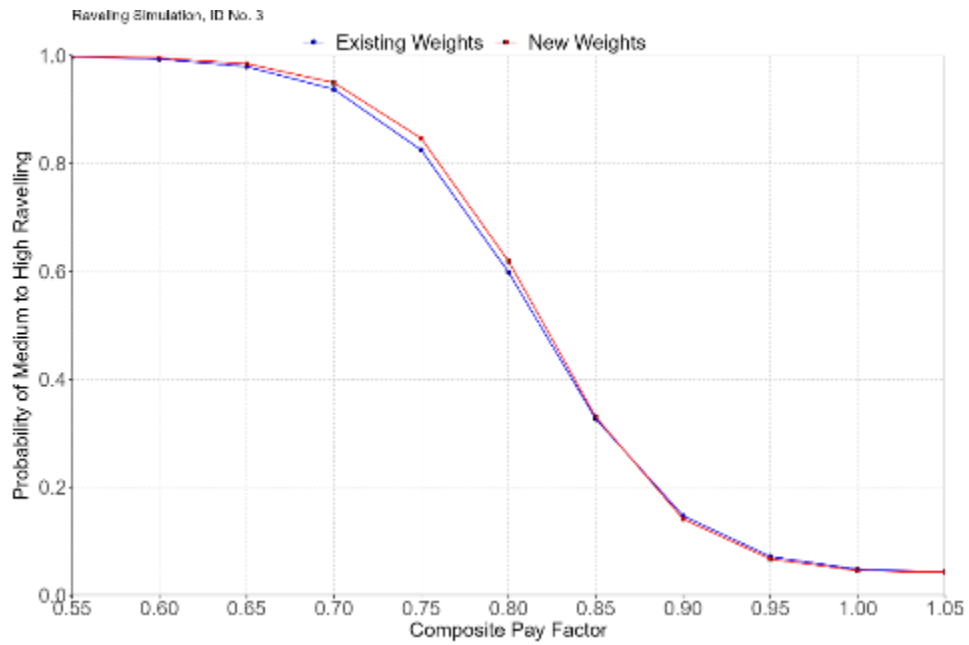


Figure S.3 Raveling Probability Curves for Open Graded Mixtures (Simulation ID 3)

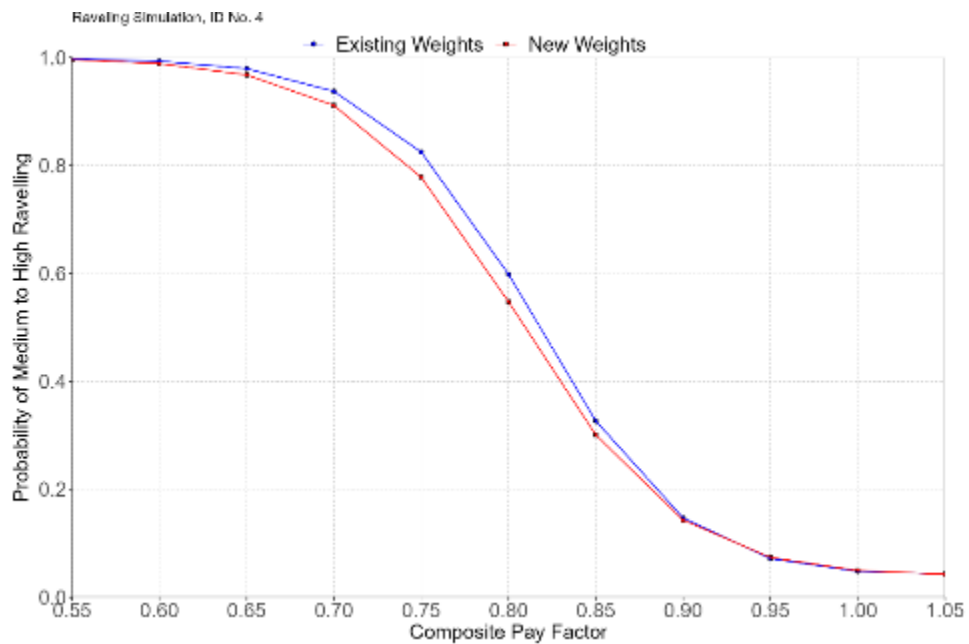


Figure S.4 Raveling Probability Curves for Open Graded Mixtures (Simulation ID 4)

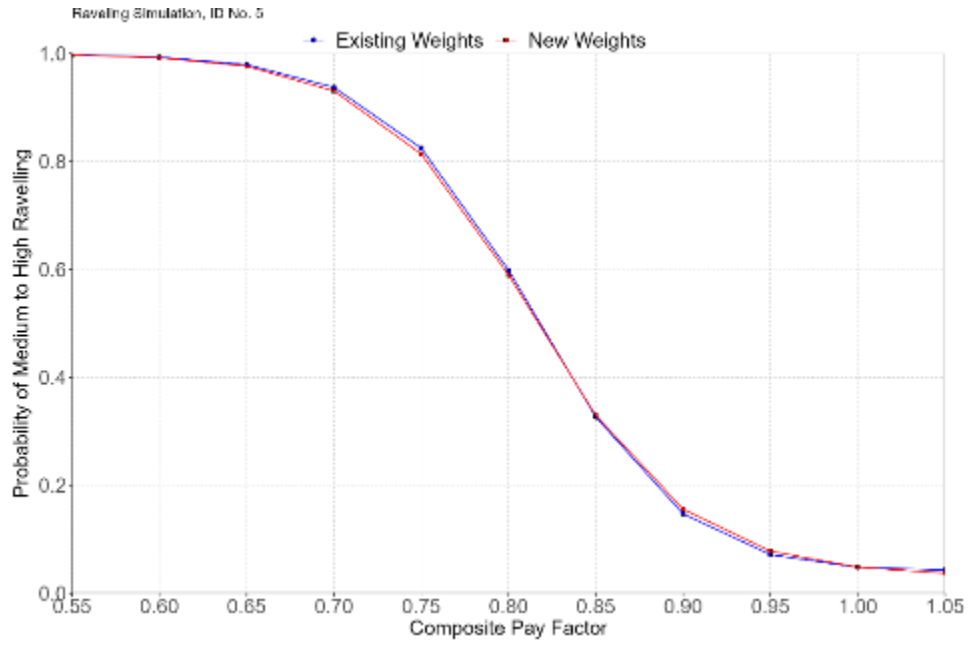


Figure S.5 Ravelling Probability Curves for Open Graded Mixtures (Simulation ID 5)

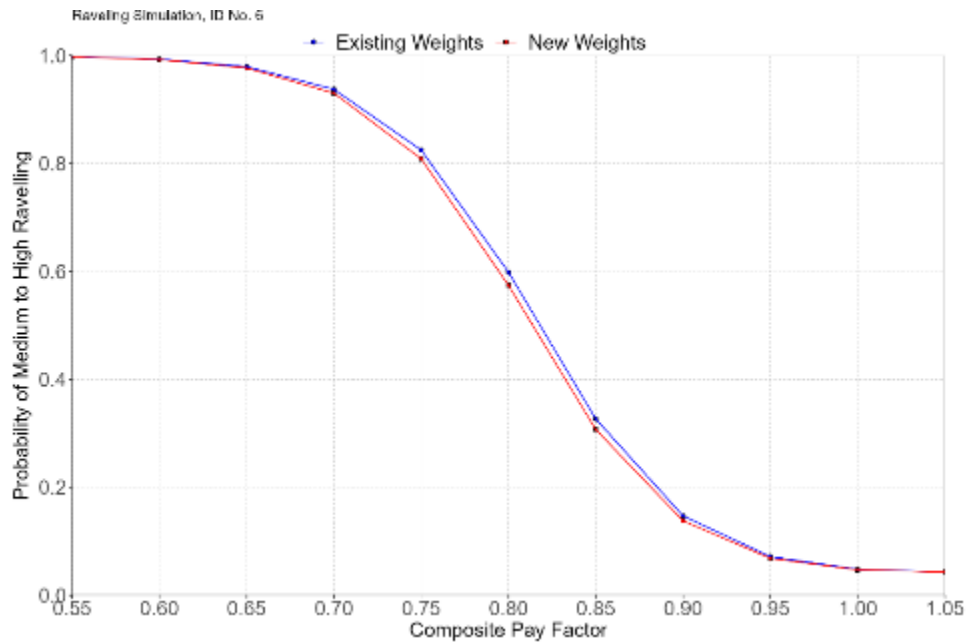


Figure S.6 Ravelling Probability Curves for Open Graded Mixtures (Simulation ID 6)

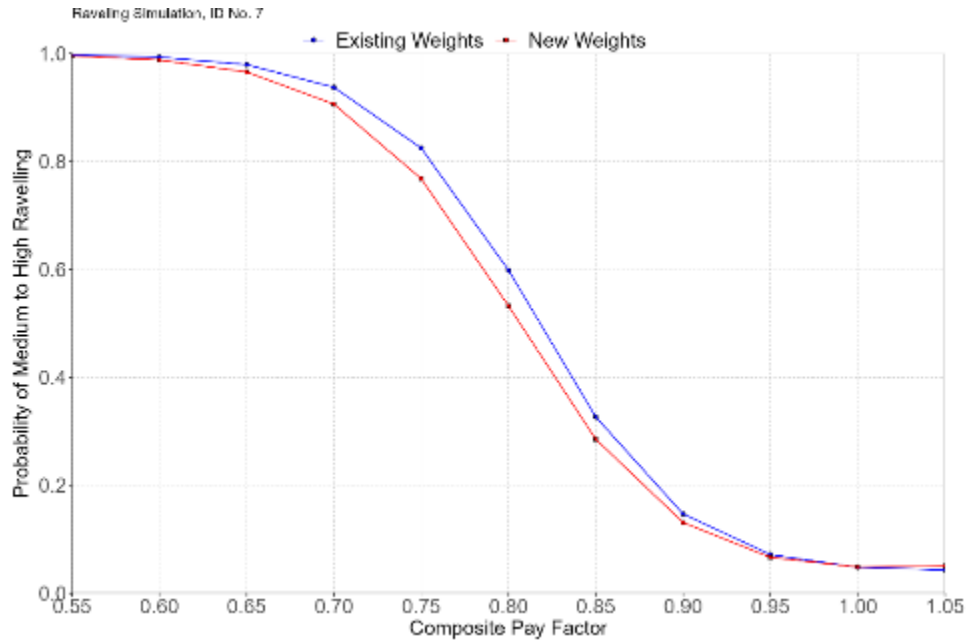


Figure S.7 Ravelling Probability Curves for Open Graded Mixtures (Simulation ID 7)

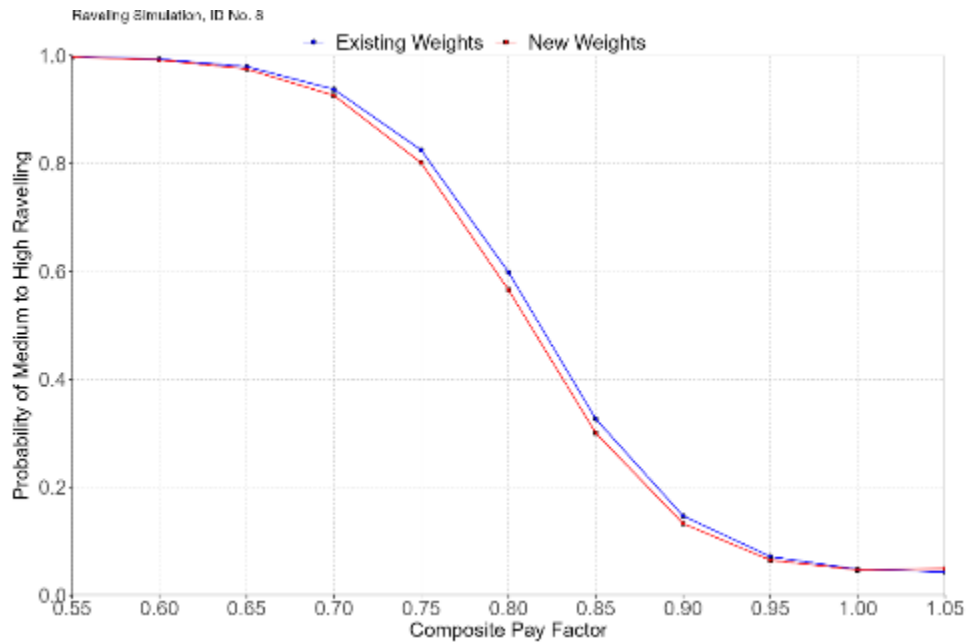


Figure S.8 Ravelling Probability Curves for Open Graded Mixtures (Simulation ID 8)

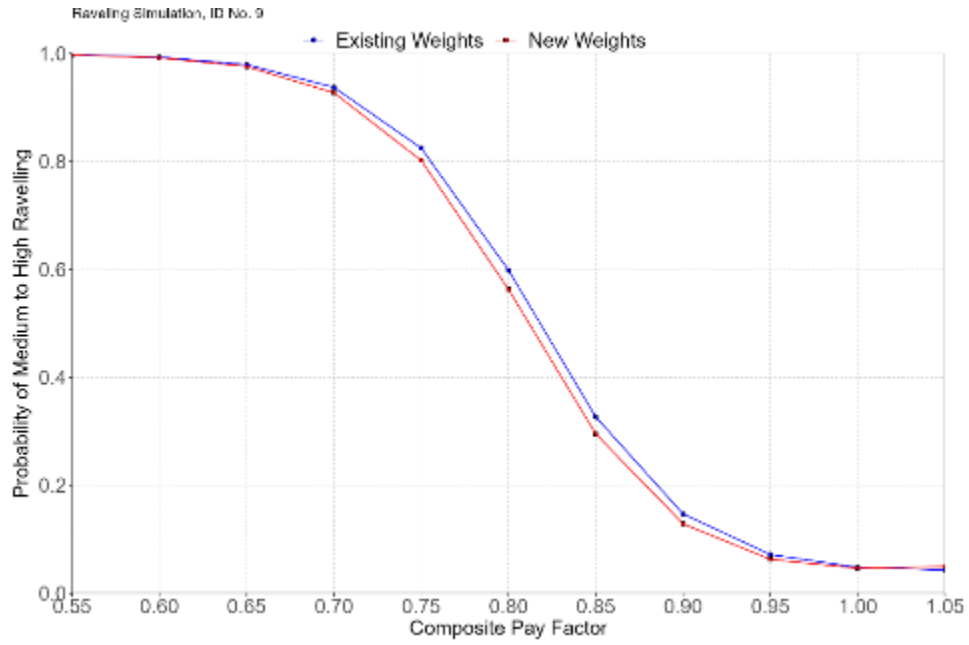


Figure S.9 Ravelling Probability Curves for Open Graded Mixtures (Simulation ID 9)

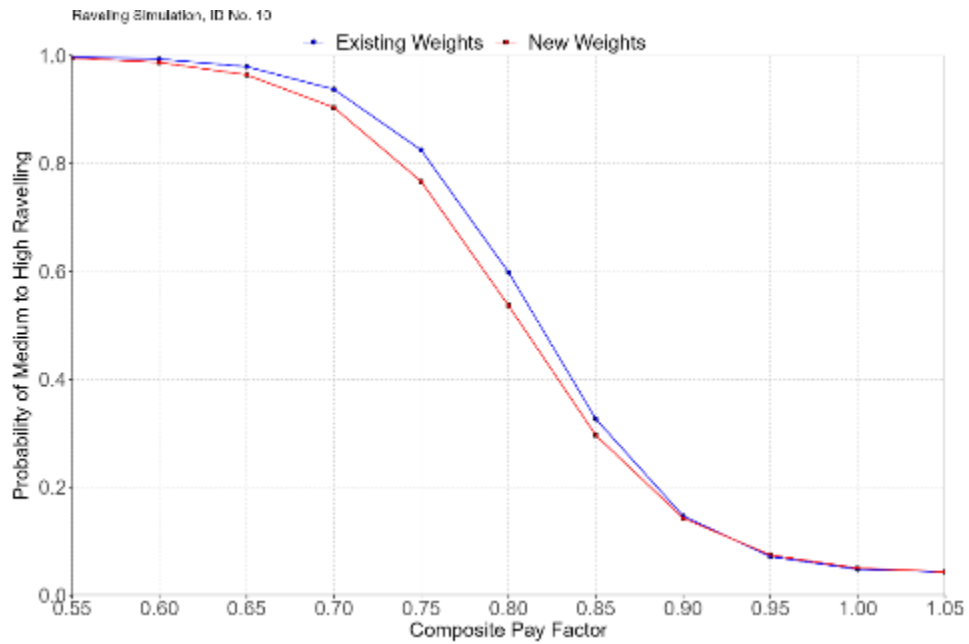


Figure S.10 Ravelling Probability Curves for Open Graded Mixtures (Simulation ID 10)

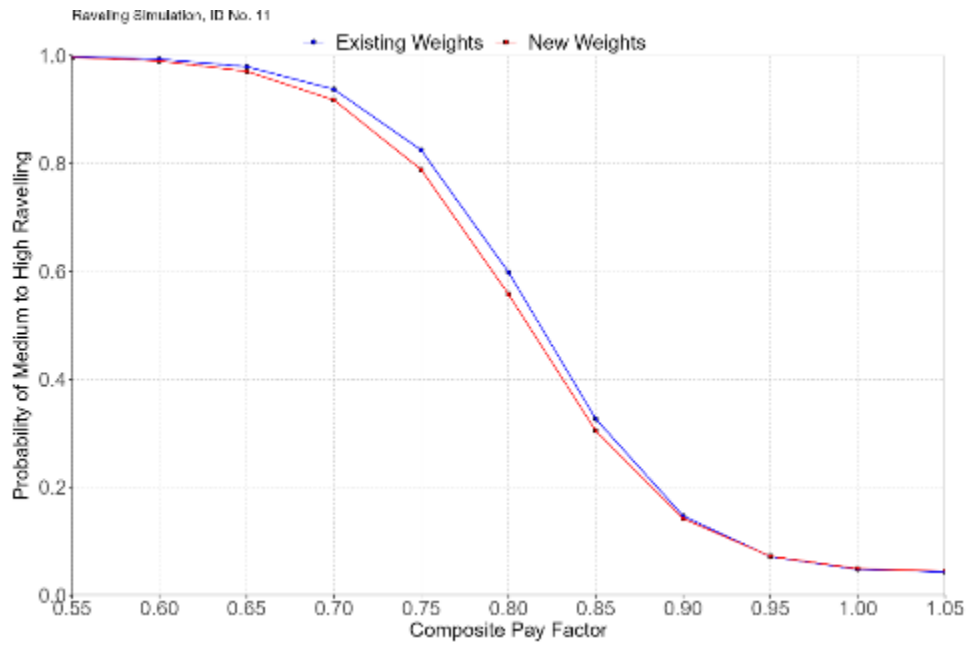


Figure S.11 Raveling Probability Curves for Open Graded Mixtures (Simulation ID 11)

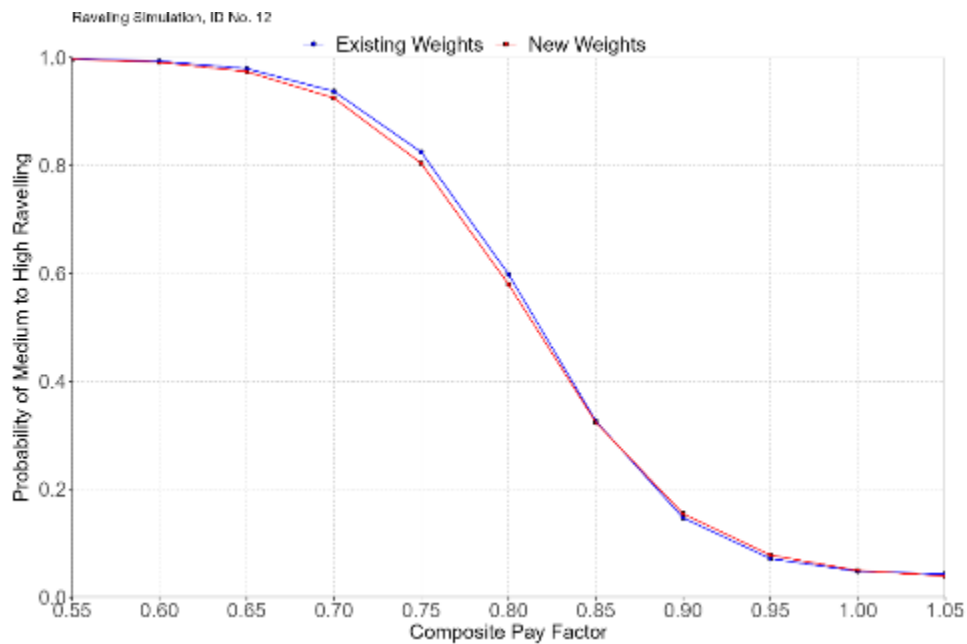


Figure S.12 Raveling Probability Curves for Open Graded Mixtures (Simulation ID 12)