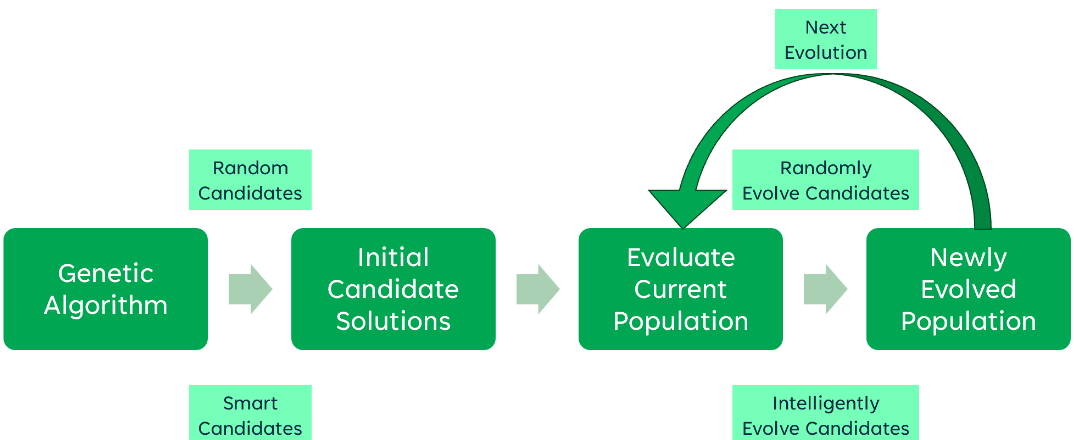
Optimizing Missouri's Statewide Transportation Improvement Program Letting and Construction Schedule



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16. Abstract
This study evaluated how Missouri's annual letting calendar could be structured to improve competition and lower award costs while remaining feasible under existing policies and delivery practices. Historical bid outcomes were used to estimate monthly "performance curves" that related workload share to observed price behavior. A genetic algorithm then assigned projects across roughly eleven monthly lettings to minimize expected awards, subject to practical constraints. Contractor capacity was reflected implicitly in the curves and examined explicitly through a backlog based probabilistic bidding check.

Optimized schedules consistently reduced expected annual awards. Depending on fiscal year and the constraint set, scaled savings were estimated to range from about $5M to $105M. On an average basis this represented approximately 6.3 to 8 percent of the total program. Monte Carlo analyses tests supported the robustness of these results. The slippage experiments indicated that delaying about ten percent of projects increased annual costs by roughly 2.0 to 3.0 percent of total program.

Policy implications were direct. Lettings should be targeted toward fall and winter where feasible, monthly volumes should be smoothed rather than concentrated late in the fiscal year, adherence to the published schedule should be reinforced, and longer, reliable advertising lead times should be provided. A lightweight tool based on performance curves and a concise key performance indicators dashboard was recommended for a pilot season. Because the method relied on standard program and bid data, it is generalizable to other state DOTs seeking to protect competition and purchasing power while fitting local constraints.

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- Indiana DOT: Louis Feagans

As well as contributions from:

- Missouri/ Kansas Chapter American Concrete Pavement Association (ACPA): Mark Shelton
- Missouri Asphalt Pavement Association (MAPA): Dale Williams

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List of Abbreviations and Acronyms

23 CFR 420 ....Code of Federal Regulations, Title 23, Part 420

AASHTO ....American Association of State Highway and Transportation Officials

ACPA..........................American Concrete Pavement Association

DBE ....Disadvantaged Business Enterprise

DOT ....Department of Transportation

FHWA ....Federal Highway Administration

GA..............................Genetic Algorithm

JOC ....Job Order Contract

KDOT ....Kansas Department of Transportation

LINC-D ....Linking Infrastructure Challenge with Data (Nebraska DOT initiative)

MAPA ....Missouri Asphalt Pavement Association

MoDOT ....Missouri Department of Transportation

NDOT.........................Nebraska Department of Transportation

NHCCI ....National Highway Construction Cost Index

NCHRP ....National Cooperative Highway Research Program

NTL ....National Transportation Library

ROSA P.......................Repository & Open Science Access Portal

SHA ....State Highway Agency

SSGL...........................Signing, Striping, Guardrail, and Lighting

STIP............................Statewide Transportation Improvement Program

TAC ....Technical Advisory Committee

TRT ....Transportation Research Thesaurus

FY...............................Fiscal Year

KPI ....Key Performance Indicators

Executive Summary

This study was undertaken to determine how Missouri's project letting calendar could be optimized to improve competition and lower award costs while remaining feasible within existing policies and delivery practices and accounting for contractor backlog. The scope included an empirical review of historical bids and awards; development of a practical scheduling framework; and evaluation of alternative annual letting patterns with and without additional policy constraints.

This research implements a simple and transparent analytical approach. Historical "performance curves" were estimated that relate monthly workload to observed bid outcomes. These curves were used to assign probably costs to candidate monthly project packages. An optimization algorithm then assigned projects across eleven monthly lettings to minimize expected costs while honoring real constraints such as district balance, project-type timing targets, treatment of large projects and bundles, and avoidance of July lettings. Contractor capacity was incorporated in two ways: first, implicitly through the historical performance curves that reflect market congestion; second, explicitly through a backlog proxy and a probabilistic bidding experiment that varied bids as contractors approached capacity.

Optimized schedules lowered expected annual award totals in every case tested. With minimal constraints that preserved only historical monthly shares, annual scaled savings ranged roughly from $22 million to $105 million, with a median near $68 million (about eight percent of the program). With a fully balanced set that also respected district limits, large project considerations, and project type targets, scaled savings remained material, ranging roughly from $4.5 million to $79 million, with a median near $53 million (about 6.3 percent of program). The difference between these medians represented the expected cost of adhering to traditional letting approach. Additional uncertainty analysis and schedule-slippage stress testing reinforced these findings.

The findings are clear. To reduce costs, lettings should be targeted toward fall and winter where feasible, with monthly volumes smoothed rather than concentrated late in the fiscal year. Adherence to the schedule should be reinforced, given the measurable cost of slippage. In the near term, month-by-type-by-district heatmaps can guide decisions even without automation. A lightweight tool that operationalizes the performance-curve method, coupled with a concise key performance indicators (KPI) dashboard (average bids, percent difference from estimate, market-backlog proxy, variance to monthly targets), is recommended for a pilot season to calibrate parameters and confirm savings in practice.

Because the method relies on standard program and bid data, it is generalizable. Any state DOT with comparable records could construct performance curves, test scenarios, and adopt a calibrated schedule that protects competition and purchasing power while fitting local constraints, with or without an explicit contractor backlog module.

1. Introduction

1.1. Background

State Departments of Transportation (DOTs) face increasing complexity in managing project letting schedules, contractor workloads, and funding allocations, particularly in the context of multi-year Statewide Transportation Improvement Programs (STIPs). As stewards over a $9.9 billion five-year STIP (MoDOT, 2025), small improvements in MoDOT's letting calendar and construction sequencing can translate into outsized returns for taxpayers. Modest shifts in when projects are advertised and how work is packaged can improve competition. Empirically, more bidders are associated with lower prices (Shrestha and Pradhananga 2010). A complementary capacity dynamic is that as contractors' project backlog and capacity utilization rises, participation tends to fall and costs increase. In repeated highway auctions, firms with low backlog are about twice as likely to bid as firms with high backlog (Jofre-Bonet and Pesendorfer 2001), and cross-market evidence shows prices fall when backlogs drop and competition increases (Gugler, Weichselbaumer, and Zulehner 2015).

Letting month and season also matters. Agencies report that bidder availability is higher and bid prices typically more competitive in off-season lettings, whereas late-season lettings are least favorable as contractors price risk into the next year (Iowa Department of Transportation 2025; Wisconsin Department of Transportation 2020). Further review of MoDOT's own data indicates that a significant proportion of projects are let in early summer months at the end of the state fiscal year (e.g. in May), when bid prices have been shown to be higher than off-season (winter) months.

At the same time, the funding base that underwrites these programs is under pressure. Missouri faces the same dynamics as other states and manages one of the nation's largest state systems. In 1952, the department assumed responsibility for nearly 12,000 miles of county highways, dramatically expanding its network (MoDOT, n.d.-a). Today, MoDOT's Citizen's Guide to Transportation Funding notes Missouri ranks 48th nationally in revenue per mile, reflecting a large system funded with historically low fuel-tax rates (MoDOT, n.d.-b). These challenges are being further compounded on the cost side, the Federal Highway Administration's (FHWA) National Highway Construction Cost Index (NHCCI) shows seasonally adjusted highway construction prices have risen by 67 percent between Q1 2021 and Q1 2024 (FHWA, n.d.-a), underscoring why timing choices that attract more bidders or avoid peak-cost windows can preserve real buying power.

MoDOT's current mechanisms for determining contractor workload and project scheduling rely on tentative letting schedules, which are frequently adjusted due to market conditions, staffing constraints, funding and other external factors. The agency has observed a trend toward increased outsourcing of routine maintenance activities, such as sign repair and striping, as internal staffing resources become more constrained.

This research effort was initiated in response to these operational challenges, with the aim of developing actionable policy recommendations and proof-of-concept tools to support more effective project scheduling and resource allocation throughout the year to improve competition and reduce award costs, and for developing a practical way to gauge contractor capacity so schedules can be adjusted to promote bidder participation.

1.2. Project Goals and Objectives

This project's goal is to provide evidence-based guidance and practical tools to optimize MoDOT's letting and construction schedules. An optimized schedule is to be done in a manner that the program attracts more bidders, lowers award costs, and improves delivery reliability while respecting funding, readiness, seasonality, and policy constraints.

An important distinction for this research effort is that the research was aimed to focus on optimizing the letting schedule, and not the bundling of projects, as MoDOT has a concurrent effort focused on project bundling. As defined by FHWA (FHWA, n.d.-b), project bundling is the practice of combining projects to accelerate delivery, reduce costs, and increase efficiency by combining multiple projects into a single contract. This definition is expanded to include multiple contracts that are to be let together. This research focuses on structuring when projects are advertised and how they are grouped across the months of the year.

The objectives to be completed as part of this project are outlined below:

Literature and Practice Review: Synthesize national research and peer DOT practices on letting calendars, competition, and contractor capacity. Interview with peer agencies and the contractor community to identify successes and strategies MoDOT can use to optimize letting and track contractor capacity.

Data Assembly and Curation: Build an analysis-ready historical dataset of MoDOT lettings and awards. Standardize project attributes, classify project types, and engineer timing and capacity variables. Provide a data dictionary and refresh instructions.

Exploratory Analysis and Screening Models: Quantify how timing, project type, capacity and seasonality correlate to bidder participation and award variance versus programmed values. Run sensitivity checks (e.g., COVID-era years) and identify levers MoDOT can influence.

Letting Optimization Demonstrations: Translate findings into simple rules-of-thumb (e.g. targets on monthly dollars, constraints for when to let certain work types, guardrails to avoid letting large projects at high-cost windows, or all of one District's in a single month). Pilot a constrained optimization prototype to illustrate program-level improvements that can be generalized to future fiscal years and other public agencies. Provide sensitivity tests for optimization results.

Policy Recommendations: Develop draft policy recommendations to optimize the planning and scheduling of future transportation project start dates. Also develop draft policy recommendations to optimize contractor workload management by balancing timing and resources.

Reporting: Deliver a final report, research summary, cleaned datasets with dictionary, code repository, and next steps required for converting the demoed prototype into a future tool for use in developing MoDOT's annual fiscal year (FY) letting schedule.

Through these objectives, this research equips MoDOT with practical, data-driven methods that range from straightforward scheduling rules to a usable prototype methodology for balancing monthly lettings, strengthening bidder turnout and preserving purchasing power while fitting within current processes. It also advances the thesis that a systematic, data-driven approach to optimizing letting schedules, grounded in empirical analysis of historical data, contractor capacity, and market conditions, can materially improve competition, reduce costs, and enhance the efficiency of Missouri's transportation investments. By developing policy recommendations and engaging stakeholders throughout the process, the project provides actionable strategies to maximize the effectiveness of the STIP and deliver greater value to the public.

1.3. Report Organization

This report is organized as follows:

Chapter 1: Introduction. States the research's background and project goals and objectives.

Chapter 2: Literature and Practice Review. Summarizes existing letting practice, national practice on letting and monitoring contractor workloads, and insights from peer agency and contractor community interviews.

Chapter 3: Exploratory Analysis. Documents data sources and processing, describes the exploratory analyses, and summarizes findings that are relevant for optimization analysis and/or policy recommendations.

Chapter 4: Optimization Analysis. Outlines optimization methodology, scenario design, sensitivity testing, evaluation metrics, and findings from algorithm outputs.

Chapter 5: Policy Recommendations and Implementation. Translates findings into guidance on when to advertise projects and how to estimate and manage contractor workload.

Chapter 6: Conclusions. Distills key takeaways, limitations, and practical next steps for integrating the approach into future letting cycles.

Chapter 7: References.

The report also contains the following appendices:

Appendix A: Performance Curves and Heatmaps
Appendix B: Mock Tool User Interface

2. Literature and Practice Review

A focused literature review was conducted to frame letting practice and contractor workload management. MoDOT's practices were documented from publicly available materials. Peer-state approaches and national guidance on scheduling, procurement, and contractor-capacity tracking were examined through agency publications and industry reports. Insights were supplemented by interviews with peer states and the contractor community to validate practices and identify transferable methods for balancing monthly lettings and monitoring backlog.

2.1. MoDOT Existing Letting Practices

Publicly available MoDOT materials were reviewed to document current letting practices and constraints. Core sources included the STIP, historic letting calendars, bid-tab archives, program guidance on MoDOT.org, and procurement materials. Findings were corroborated through interviews with planning and programming, district staff, and construction contract services.

MoDOT currently holds its project lettings on the third Friday of every month with a tentative letting in July. The awards are typically awarded on the first Wednesday of each month after commission approval. To help contractors better plan their staffing and work schedule, MoDOT also releases a tentative six-month letting schedule. Additionally, MoDOT does implement some project bundling. For example, it was shared in interviews with MoDOT that Southwest District often meets with four different asphalt contractor groups through the Fall to discuss projects and potential bundles and likely cost impacts to MoDOT.

Contractors seeking to do business with MoDOT are required to follow a detailed bidding checklist to ensure compliance. These requirements include submitting items such as a contractor questionnaire, bidding documents, and bonds (MoDOT, n.d.-c).

There are, of course, constraints that add complexity to the letting process and timelines. For example, MoDOT noted that funding constraints require projects to adhere to strict timelines, especially for specific initiatives like the Governor's Rural Routes Resurfacing program. Furthermore, project cost is still a major factor that is heavily impacted by inflation and material costs such as asphalt and concrete prices.

However, these constraints do present some potential for opportunities. Interviews with MoDOT staff found that one potential strategy is to improve the scheduling of roadway and bridge projects by aligning them with available funding streams and addressing logistical constraints.

Moreover, MoDOT staff noted that data systems like AASHTOWare and district estimates can provide valuable insights for project planning and error checking because they offer greater accuracy than the values outlined in the STIP, as projects and scopes are subject to change.

Staff also identified the construction division's records on contractor capacity as a resource that could help address project management challenges.

2.2. Industry Practice on Letting and Contractor Workload

The research team explored several key sources for information, including National Cooperative Highway Research Program (NCHRP) publications, FHWA reports, academic research studies, industry publications, and prior work completed by High Street.

2.2.1. Kansas DOT (KDOT) Construction Bid Analysis

The Kansas Department of Transportation (KDOT) commissioned an analysis of its contractor bidding data to evaluate the competitiveness and cost-effectiveness of its contracting environment (Egge, 2020). The analysis aimed to answer two primary questions: whether KDOT has a healthy contracting environment and if it is receiving competitive bid prices. The analysis revealed several important trends regarding KDOT’s bidding environment that can be applicable across all state DOTs.

- **Declining Competition:** There has been a noticeable reduction in the number of active contractors bidding on KDOT projects, which aligns with broader national trends. This decline in competition has led to fewer bids per project, which is associated with higher award prices.
- **Cost Competitiveness:** The study found that KDOT's cost competitiveness varied by district and work type. Projects in District 1, for example, tended to face higher costs for certain pay items like hot mix asphalt and rock excavation.
- **Impact of Program Size on Competition:** KDOT’s program size reduced significantly in FY 2017, resulting in many contractors leaving or downsizing their operations. As a result, when KDOT’s program ramped up again, the decreased contractor capacity caused fewer bids at higher prices.

2.2.2. Nebraska DOT (NDOT) Linking Infrastructure Challenge with Data (LINC-D)

The Nebraska Department of Transportation (NDOT) Attracting Bids study (High Street, 2018) was conducted to explore strategies for increasing contractor participation in project bidding. Its primary objective was to identify factors associated with the number of bids received, with the broader aim of enhancing competition and reducing project costs.

The analysis identified several effective approaches: bundling projects, distributing them evenly across different lettings and seasons, extending advertising periods, and providing greater flexibility in contract working days all helped attract more contractors to participate. Notably, the study found that including more projects in a single letting resulted in fewer bids per project. Furthermore, each additional bid led to an average four percent reduction in the awarded project price. Projects with a disadvantaged business enterprise (DBE) goal of up to four percent also received more bids than those without a DBE goal.

Further, in April 2020, NDOT examined recent trends in contractor bid pricing for major construction projects (High Street, 2020). This study was prompted by unexpectedly high bids received earlier that year, raising questions about whether contractor prices had increased in the aftermath of the 2019 flooding emergency response work.

The findings showed a significant surge in capital improvement project costs, with annualized inflation rates climbing as high as 12 percent, especially for earthwork, concrete, and steel. To help manage these rising expenses, the study recommended several strategies: using a shorter time frame for pay item price estimates, updating estimates for large upcoming projects to reflect current market prices, and developing a real-time inflation dashboard that tracks and revises inflation estimates based on a wider range of goods.

2.2.3. NCHRP Statewide Highway Letting Program Management (2004)

A 2004 NCHRP report on “Statewide Highway Letting Program Management” provides general background information on the typical letting process used by State Highway Agencies (SHA) (National Academies of Sciences, Engineering, and Medicine, 2004). Table 1 shows the number of states that use a particular letting frequency. The monthly letting timeline was found to be the most common frequency. The paper does not provide best practices by states and caveats that there is limited documentation available on state letting practices. However, the researchers do note that states should avoid letting large projects at the same time.

Table 1: Frequency of Project Lettings by Number of States

Frequency	Number of States
Monthly	11
Bi-weekly	4
Weekly	8
Other	5
Total	**28**

2.2.4. Contractor Trends

Contractors adjust the price of bids based on the risk associated with a project and their backlog of work. Some of the factors contractors account for are their current backlog, overhead, continual employment of key staff, relationship, future project bids, and whether they would have to hire additional workers (de Neufville and King, 1991). This risk can be realized in a three percent markup on the profit portion of the bid for projects that contractors see as high risk or when contractors do not need the work.

Similarly, a survey conducted with 400 general contractors in the US asked respondents to score 31 factors that affected their percent-markup and bid or no bid decision (Ahmad and Minkarah, 1988). “Current workload” and “need for work” ranked 6th and 11th, respectively, and are shown to be key factors in bid markups. Whereas “degree of hazard” and “degree of difficulty” were ranked 1st and 2nd. Comparatively, when looking at how influential these same factors were in determining whether a contract bid on a project, “need for work” and “current workload” ranked 2nd and 13th, respectively.

Therefore, a contractor’s current need for work, or their capacity, directly impacts their bidding decision and the percent markup on the bid. This topic of contractor capacity was a limitation that was noted in the MoDOT, peer state, and contractor interviews conducted by the research team.

2.3. Peer State and Contractor Insights

To build on the desktop research findings and gain a more nuanced understanding of peer-state letting practices and the factors contractors consider when determining whether to bid on a project, the research team conducted five in-depth interviews with state DOT practitioners and contractor associations.

2.3.1. Peer State Interviews

Three peer state DOT agencies were selected to interview: Iowa, Kansas, and Indiana. Table 2 lists the representatives interviewed at each agency. The interviews and the questions asked were designed to contextualize MoDOT’s letting process by providing insights into real world practices of how other agencies structure their letting programs, any letting or cost analysis done, and areas of improvement or solutions the agency has implemented. The questions asked are shown in Table 3 at the end of this section. The goal of these interviews is to identify opportunities for MoDOT to improve and learn about the challenges other states are facing and how they are approaching them.

Table 2: Peer State Interviewee(s)

Agency	Interviewee(s)
Iowa DOT	Deanna Maifield - Bureau Director Mark Dunn – Director, Transportation Bureau Chief of Contracts & Specifications Mark Swenson – Transportation Engineer Specialist
Kansas DOT	Allison Smith - Carbon Reduction Program Manager Gene Ingwerson - Program Controls Executive/WinCPMS Administrator Lisa Roth - Program and Project Management Analyst Colby Farlow - Director of Program and Project Management
Indiana DOT	Louis Feagans - Managing Director of Asset Management

These agencies strategically schedule project lettings to match construction seasons, contractor availability, and regional weather patterns. For example, Iowa DOT holds monthly lettings and spaces out large projects between October and March, allowing contractors sufficient time for bidding. They also adjust project completion dates based on county climate differences and are flexible with scheduling to accommodate contractor needs. For example, Kansas DOT prioritizes letting pavement projects before December to maximize competition. Kansas also uses project bundling tools in AASHTOWare Preconstruction to streamline processes. Similarly, Indiana DOT finds its best bidding window between October and February, and coordinates geographically related projects for efficient traffic management.

Contractor capacity was a consistent theme brought up by these agencies due to its impact on the number and price of bids submitted by contractors. However, there are data gaps in the information DOT's have on contractor capacity. Kansas DOT noted that while they do not have contractor capacity information, they do track the amount of work a contractor has in terms of projects and total contract amount. Iowa DOT also added that the bid package size is a key factor in maximizing the number of bidders. The bid package should be large enough to solicit bids, but not too large so that it exceeds their bidding capacity.

Table 3: Peer State Interview Questions

Question Category	Questions
Current Processes	• Can you describe the DOT's current letting process and the role you play in it? • What kind of historical precedent is there for when certain types of jobs are released? • Does the DOT have a process/documentation for bundling projects by type or on a corridor? • What flexibility do staff have in moving projects between construction years (or lets)? • Are there any other rules/restrictions for moving projects?
Costs	• Are there fluctuations in cost due to geography, job type, or other factors? • Can you describe the current cost estimation process? • How was the current methodology? • Were there other options considered? If so, what advantages did it present? • How was the software selected, if any? • What kind of assumptions are made about construction cost inflation?
Available Data or Analyses	• Has there been any prior analysis of letting data to determine optimal letting times? • Does the DOT have any information on contractor workload/capacity when finalizing lettings? • Is there data on the number of change orders or performance for each project or job type?
Areas for Improvement	• Are there specific optimizations in the current processes that you would like to see (e.g. maximize projects, smooth out project letting, cost savings, staff time saving, other efficiencies) • Has the DOT observed any quality issues relative to low-cost bidders? • Are there best practices from other state DOTs you're interested in exploring? • Does the DOT have any restrictions or approvals needed to make changes to the letting process? • Do you have any other ideas on improvements? Are there specific pain points in the current process?

2.3.2. Contractor Interviews

Representatives from two contractor associations, the American Concrete Pavement Association (ACPA) and the Missouri Asphalt Pavement Association (MAPA), were also interviewed. Table 4 lists the representatives interviewed at each association. The interviews and questions aimed to reveal how contractor associations determine when to bid on projects, how they manage their workforce and capacity, and what MoDOT can do to help contractors. The questions are shown in Table 5. The goal of these interviews is to identify opportunities for MoDOT to learn about the challenges contractor associations are facing and what MoDOT can do to help.

Table 4: Contractor Interviewee(s)

Association	Interviewee(s)
American Concrete Pavement Association (APCA)	Mark Shelton - Field Engineer MO/KS Chapter
Missouri Asphalt Pavement Association (MAPA)	Dale Williams - Executive Director

Both associations agreed that project timelines, work type, and a consistent and predictable flow of projects are key to contractors' bidding decisions. Legislative actions, like gas tax increases, influence bidding and pricing as well. MAPA highlighted that flexible scheduling, especially fall lettings, helps contractors plan ahead and lower costs. Contractors with their own material sources are more competitive due to operational efficiencies.

In terms of contractor capacity, they noted that contractors can expand operations to meet demand, but face labor and equipment shortages. MAPA added that contractors are often limited by plant and workforce capacity. Additionally, the distance between quarries/plants and job sites affects efficiency and costs.

Both groups suggested MoDOT could improve communication on project timing. The ACPA suggests more lead-time details, while MAPA recommends including more project specifics in the STIP. However, both associations noted their appreciation of the MoDOT Southwest District's annual meetings about upcoming projects and suggested expanding these statewide for better planning.

Table 5: Contractor Interview Questions

Question Category	Questions
Bid Decisions	• What impacts “Go vs. No Go” decision making for contractors? • Do you have enough lead time to put together a successful team/bid? • Are there any jobs you avoid for a given reason? • Do you have a preference for contracts that are larger or smaller? • What has been your experience with project bundling either by project type or corridor?
Contractor Capacity	• What can MoDOT do to help you better manage your capacity? • To what degree are contractors scaling their workforce to pursue new efforts? • When are contractors expanding into new states? How does that affect their current operations? • Is there a part of the year that is more overwhelming or undesirable for bidding? • Is the work consistent with the crews you support?
Other MoDOT Improvements	• What do you think MoDOT could do to encourage contractors to submit more bids? • Are there practices other state DOTs utilize that you think MoDOT should explore?

2.4. Implications for MoDOT

The literature, peer-state practices, and contractor interviews indicated several actionable implications for MoDOT’s scheduling, procurement, and capacity-tracking approaches. The items were framed to translate directly into optimization constraints, targets, and penalty functions, into implementable policy or process adjustments, or future data collection efforts and next steps.

Letting cadence and timing. A regular monthly cadence was affirmed and a more even distribution across months was recommended. Concentration in May was discouraged and earlier fall–winter windows (roughly October through January) were favored to align with contractor planning. A consistent and predictable calendar for industry was emphasized.

Project mix and bundle sizing. Bundling was encouraged where it created efficiency, particularly if recommended by contractors, but oversized bundles were discouraged because they reduced participation. Staggering of major bridge work after paving activity was supported. The number and size of projects per letting were to be moderated to avoid crowding bidder capacity.

Contractor capacity management. A practical proxy for capacity using awarded value was suggested. This proxy was intended to set guardrails on monthly workload, to avoid periods when the market was already busy, and to encourage placement of work when contractors sought to fill the next season’s backlog. Avoiding letting large projects simultaneously was also suggested.

Transparency and lead time for industry. Greater advance notice and specificity were encouraged, including longer advertising windows, clearer target months in the tentative schedule, and district-level quantity previews. Expansion of district briefings (e.g. annual Southwest district contractor meeting) that shares upcoming work was recommended to improve planning and participation.

Data and monitoring improvements. It was recommended that a standardized data structure be maintained and that gaps be reduced where feasible, including geocoded project and contractor plant locations, engineer's estimates versus programmed estimates or STIP estimates, and complexity and hazard indicators.

3. Exploratory Analysis

This chapter documents the data, processing, and methods used to quantify how scheduling and capacity relate to bidder participation and award outcomes, and to test schedule optimization methodologies and scenarios for MoDOT's STIP. The work followed three steps:

- Assemble an analysis-ready letting dataset
- Conduct exploratory analyses to identify actionable relationships
- Demonstrate optimization methods that minimize monthly letting costs under practical, realistic, data-informed constraints.

3.1. Data Sources and Processing

The analysis drew on three complementary MoDOT datasets covering FY 2016 through FY 2024.

1. **Bid Opening Data (2015–2024).**

   This file provided the foundational project and letting identifiers used to stitch sources together. Fields available included: proposal number, winning vendor number and name, letting number, proposed start and end dates, projects included in the proposal, counties, and routes. This data was provided by MoDOT from AASHTOWare.

2. **All Bids File (2015–2024).**

   This expanded the bid opening data with bid-market details. Fields available included: project type, the full bidder list with rank order from best to worst bid, and line-item bid tabs (item number, description, units, quantities, item prices, and item totals). These records permitted aggregation to each contractor's total bid and quick identification of predominant work items on a project. This data was provided by MoDOT from AASHTOWare.

3. **Let Results (FY 2015–FY 2024; June 2014–May 2024).**

   This file supplied program alignment and award outcomes. It indicated whether a project was in the STIP, the CALL number used to denote bundles (projects sharing a CALL were treated as one package for optimization analytics), District, programmed amount, winning bid amount, difference and percent difference from programmed amount, job order contracts (JOC) or other special project flags, and whether a project was awarded or rejected. Consistent with construction-services practice, special lettings, design-build projects, and projects let by others were excluded from the optimization analysis.

4. **Future Year STIP (FY 2027)**

   Future projects planned highway and bridge projects scheduled for letting in FY 2027 were obtained from MoDOT's website (https://www.modot.org/statewide-transportation-improvement-program-stip) in Excel format and were processed to be in the same format used for the optimization analysis. This included reducing the dataset to those with construction costs in FY 2027 (as opposed to engineering and/or right of way costs), identifying if the project was a JOC, and using the project description to determine project type.

The exploratory analysis and optimization process used a data set created through joining the sources outlined above, focusing on FY 2016 through FY 2024 to ensure temporal consistency across the datasets. After cleaning, the study covered 3,832 awarded projects. Exclusions were limited to non-comparable procurement types (e.g. design-build, projects let by other agencies, and emergency projects). Wherever reasonable, data favored inclusion and flagged edge cases for sensitivity checks rather than removing them outright.

In consultation with MoDOT, the 28 detailed work types were collapsed into five small work type groups for analysis that aimed to preserve market dynamics and align with existing letting practices and timing while simplifying comparisons:

- Pavement
- Bridge
- Signal
- Signing, Striping, Guardrail, and Lighting (SSGL)
- Other

With the integrated, cleaned data set established, and core attributes standardized, descriptive and diagnostic exploration was undertaken. Methods and findings are outlined below.

3.1.1. Data Notes and Gaps

Several constraints shaped scenario design and are acknowledged where relevant, including:

- Lack of geocoded locations beyond district
- No pit/plant proximity measures to aid contractor competitiveness analyses
- No additional data regarding project right-of-way, environmental, and utility readiness
- Engineer’s estimates were not provided. Bid performance was based on the deviation from programmed amount.
- No data from neighboring states is included. Structured access to similarly detailed information was unobtainable.

These gaps informed scenario design and are addressed in Chapter 5 recommendations.

3.2. Exploratory Analysis Methods

A structured exploratory analysis was conducted to characterize bidding activity, price behavior, and develop historical context before performing any modeling. The data was used to:

- Generate simple descriptive statistics and numeric and visual summaries.

- Profile bid counts over time, by project type, district, and month.
- Characterize historic monthly let amounts, project counts, project type proportions, and savings relative to programmed amounts.
- Review of historic contractor participation and backlog approximation.
- Quantify key line-item costs by month to estimate state capacity.
- Perform a series of regressions exploring bid count and bid savings (relative to programmed amount) in relation to month, letting project counts, backlog, district, project type proportions, and various combinations of the above.
- Develop simple tree-based machine learning algorithms (random forests) to identify variable importance.

Collectively, these diagnostics established the empirical bounds for scenario design and informed the selection of constraints, targets, and penalty functions so that parameters aligned with observed market behavior rather than generic assumptions. Numerous exploratory avenues were pursued, not all yielding usable results. Relevant and actionable findings are summarized in Chapter 4.

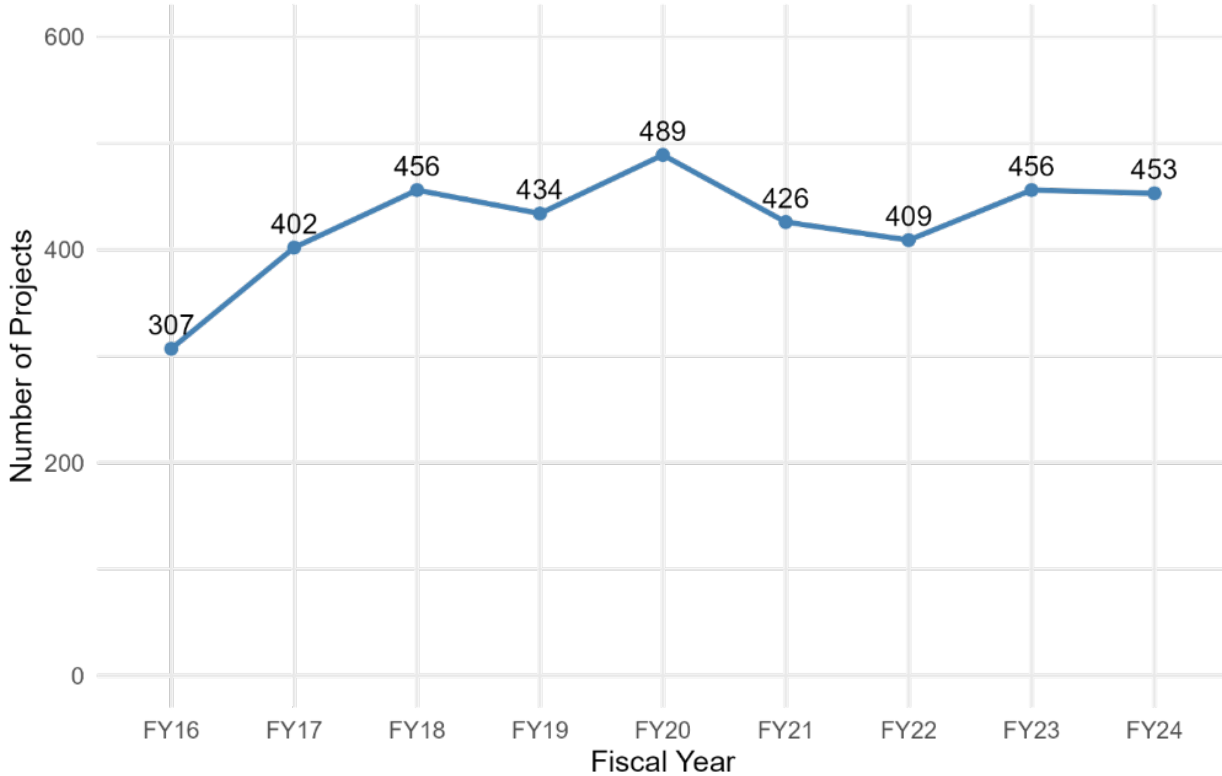
3.3. Descriptive Analysis Findings

This section distills the historical context for MoDOT’s lettings and identifies the factors that consistently shape bidder participation and pricing. It highlights the most useful empirical drivers to carry forward into optimization (e.g., timing, project mix, and scale) and summarizes contractor participation and a proxy for backlog to ground later scenarios in observed market behavior.

3.3.1. Historical Context

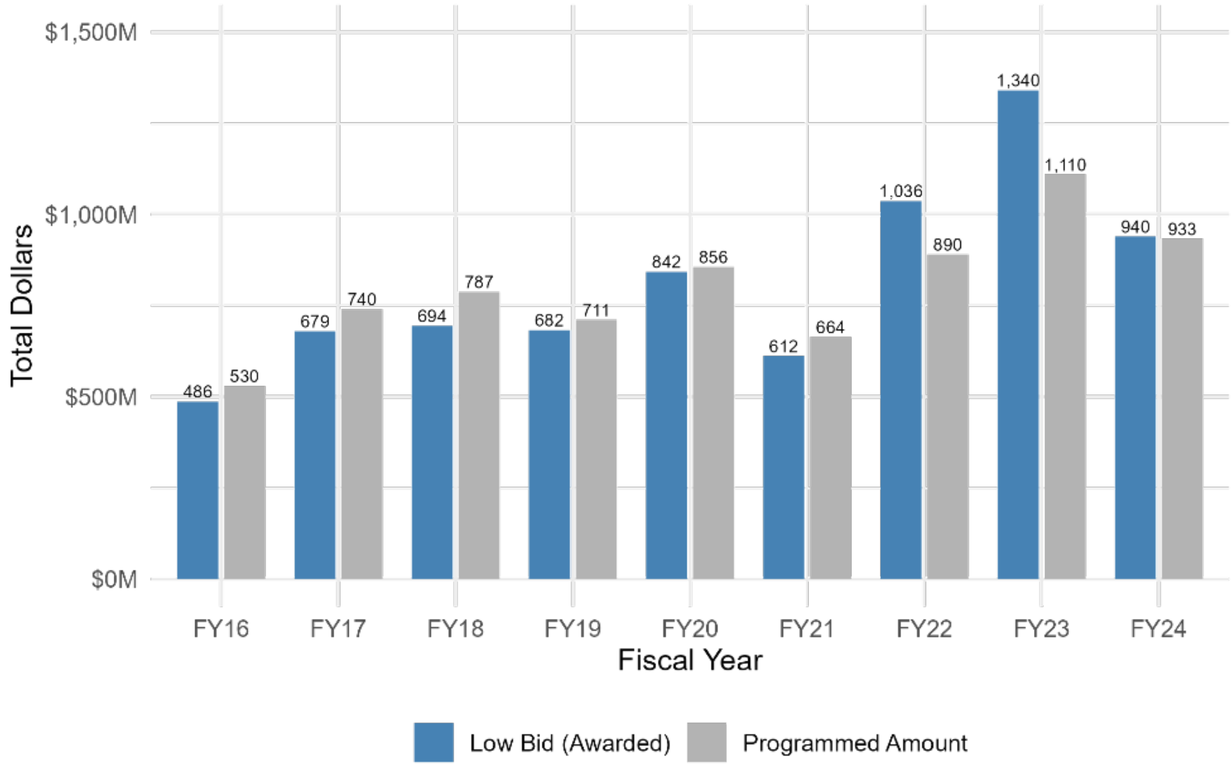
MoDOT has let between 400 and 500 hundred projects each fiscal year since 2017. The number of awarded projects rose from FY 2016 to FY 2020, then fluctuated within a relatively narrow band through FY 2024. This suggests that, while annual program size varies year to year, the agency has maintained a steady pipeline of lettings rather than bouncing between very high and very low project count years.

Figure 1. Project Count by Fiscal Year



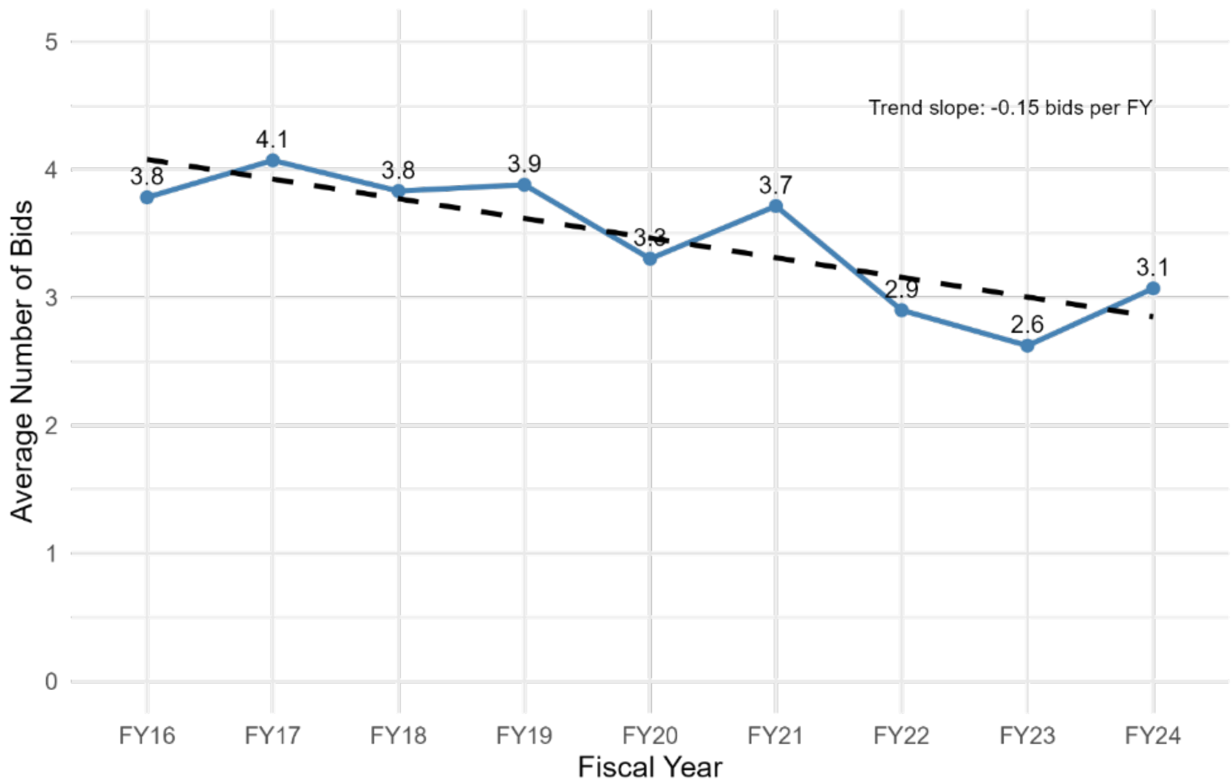
Total programmed dollars and total low-bid (awarded) dollars both increase over time as shown in Figure 2. The FY 2022 and FY 2023 post COVID years exhibit the largest dollar growth before leveling back off to more expected amounts in FY 2024, which is consistent with inflation values in the NHCCI. In most fiscal years the total low-bid amount is below the total programmed amount, indicating net savings at the program level. The size of that gap varies by year, from 11.8 percent under program in FY 2018 to 20.8 percent over program in FY 2023. Individual projects show a much wider range of outcomes, with some bids coming in substantially under and others substantially over the programmed amount.

Figure 2. Program and Award Cost by Fiscal Year



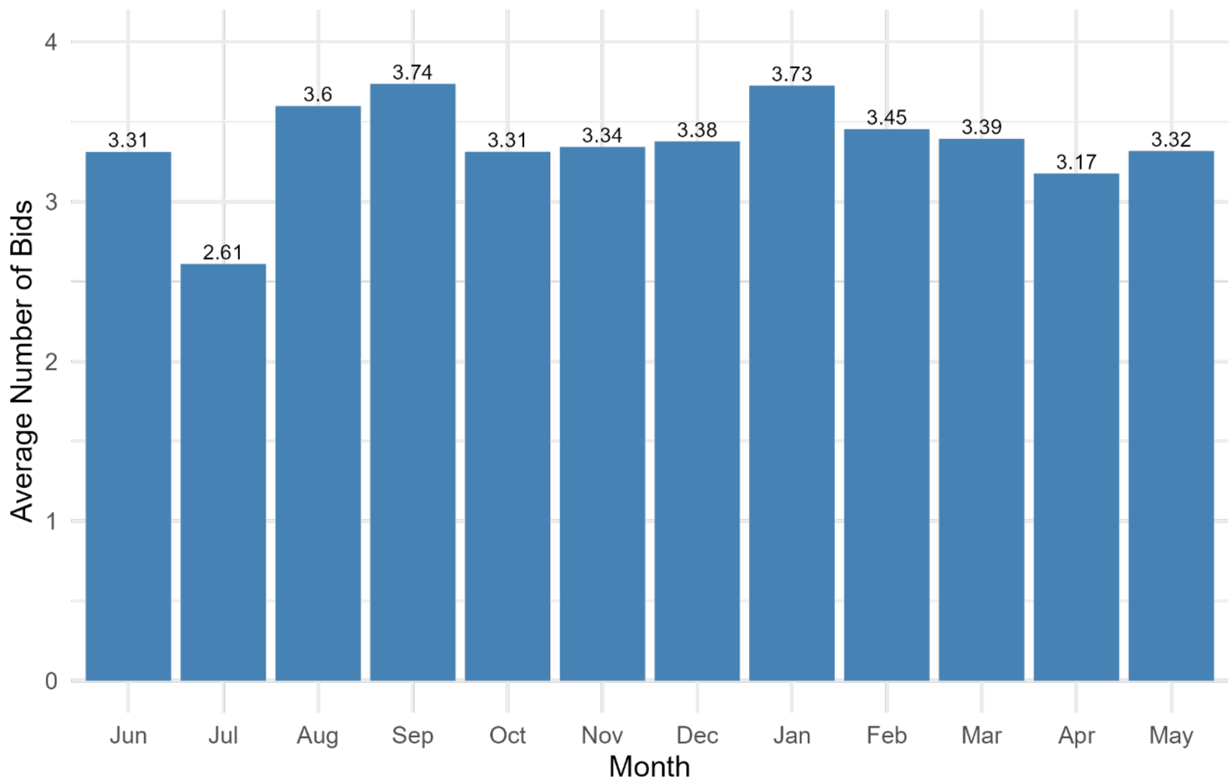
Average bidder participation per project has shifted over time. Earlier fiscal years show averages around four bids per project, followed by a gradual softening to just under three bids in the middle of the period, and then a modest rebound in the most recent year. This decline and partial recovery in average bid counts suggests periods where the competitive field was thinner, which is consistent with a tighter contractor market or higher backlog, and reinforces the value of modeling bid count explicitly.

Figure 3. Bid Count by Fiscal Year



Bidder participation also varies modestly by month within the fiscal year. Average bid counts are lowest for projects let in July (which MoDOT no long schedules regular lettings), while August, September, and January tend to attract more bidders on average. This aligns with the information received from the contracting community that they are more likely to bid on projects near the end or just after construction season as they look to fill up their backlog for the following construction season. While MoDOT tends to let more projects in October through March and May, as shown in Figure 5, contractors should have a good handle on their backlog by the time the January letting occurs. The marked bump in bid count is suspected to be caused by firms missing on bids earlier in the fall/winter letting season still looking to fill up backlog for the following construction season. Although the month-to-month differences are not dramatic, they are systematic enough to justify including letting month as a driver in the optimization analysis, especially when balancing workloads and avoiding periods of persistently lower competition.

Figure 4. Average Bid by Month



MoDOT’s letting volume is also highly seasonal. The average number of projects let per month is lowest in early summer then ramps up through the fall, peaking in October through January, before tapering off again in late spring. Additionally, it should be noted that MoDOT typically experiences both a high quantity in the number of projects and dollar value let in May (see Figure 5 and Figure 6). It has been expressed by MoDOT that this is suboptimal as prices are perceived to be higher given the project counts/value, and that contractor’s backlogs are full going into the construction season. To date this has been hard to avoid as projects are let here as it is the last chance to let them before the end of the fiscal year. This pattern shows that both contractors and MoDOT experience the heaviest workloads in the middle of the fiscal year, which is important context for later optimization scenarios that aim to avoid over-concentrating lettings in already busy months. It should be noted that there is data for July lettings as they have occurred historically. However, the data shows lower bid counts received.

Figure 5. Average Project Count by Month

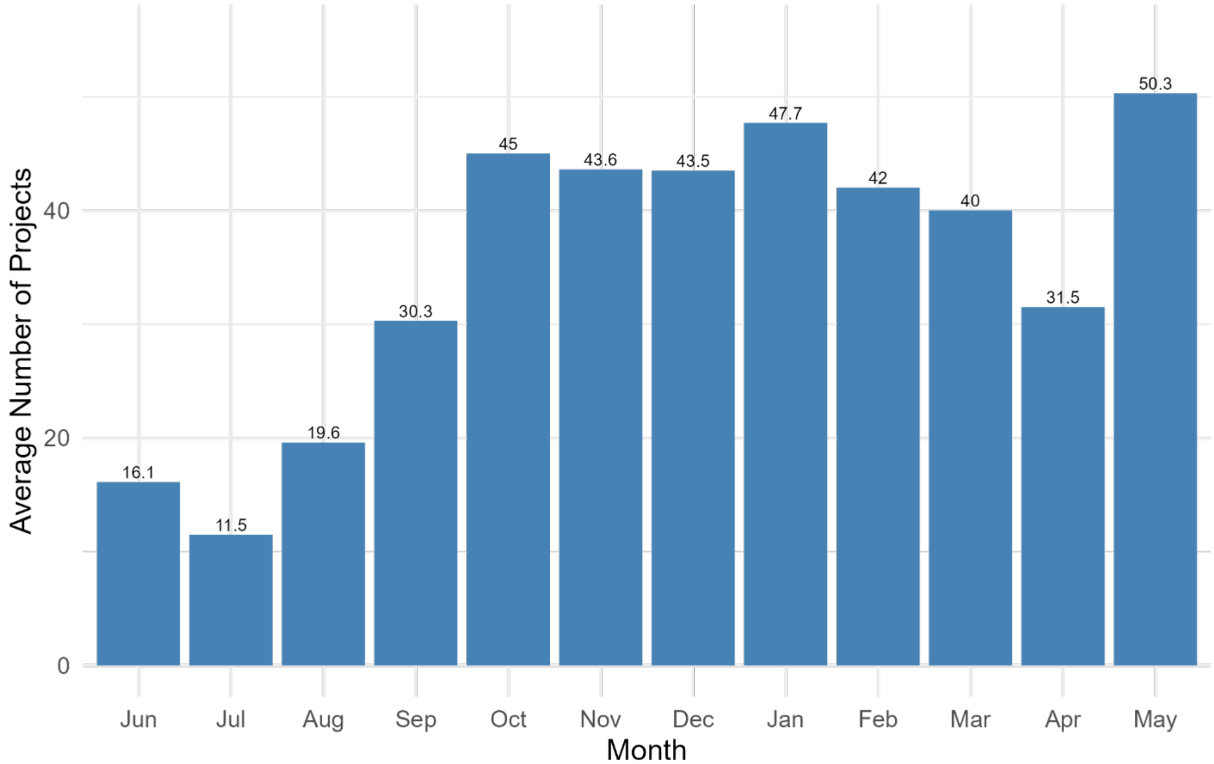
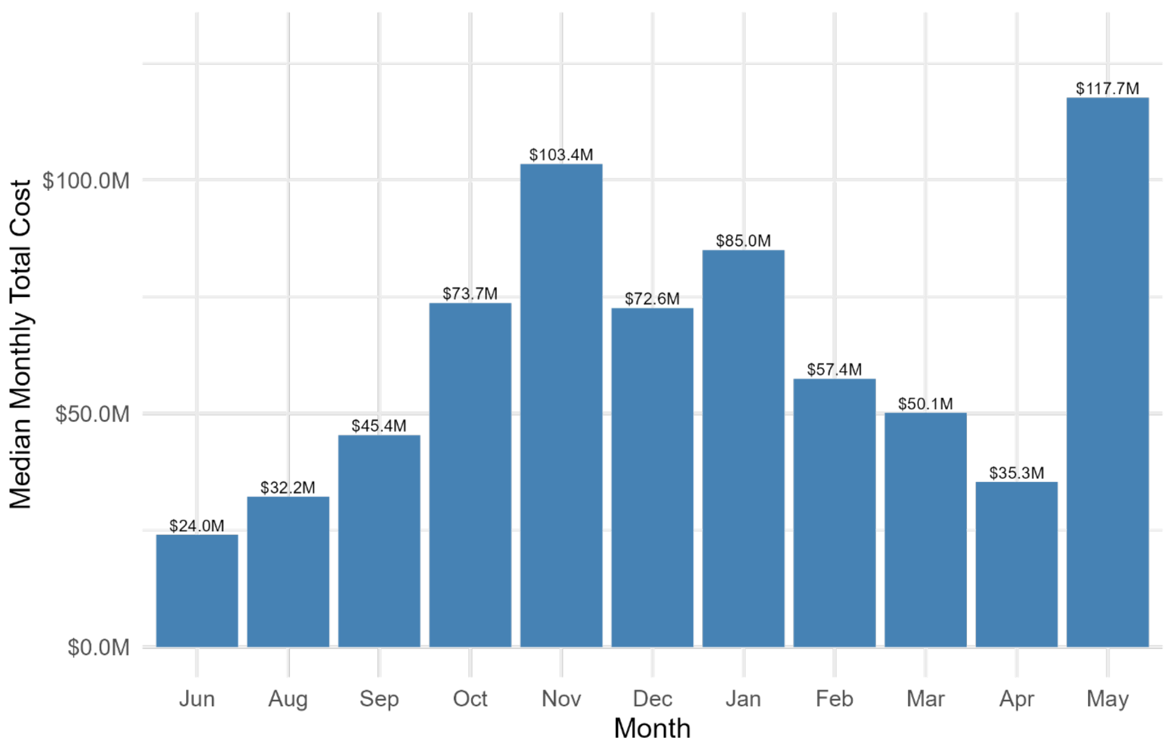


Figure 6. Median Total Award Value by Month



Median monthly letting volume also shows a clear seasonal pattern. Across fiscal years, total awarded dollars per month are smallest in early summer then ramp up through the fall. Monthly totals remain relatively high through the winter and taper off through the spring. There are pronounced peaks in November and May, which correspond with projects slipping and getting let before the end of the federal fiscal year in November, and state fiscal year in May. This suggests that MoDOT does focus lettings based on contractor feedback and construction offseason, but out of necessity is forced to let during specific months due to budgetary constraints. This is an important consideration when evaluating contractor capacity and designing more even letting schedules.

Median monthly dollar values were aggregated and are shown in the 'Median % of FY' column in Table 6. Median monthly dollar values were used as mean monthly dollar values created large skews within month if a single large project was let during that month at any point in the historical data. The median across fiscal years shows many of the years had no projects let in July. Based on guidance from MoDOT, these monthly values were adjusted such that target percentages did not include any monthly let values in July. This was completed by equally distributing July let values for FYs with a July letting across the other 11 months of the year and recomputing the median. Finally, 'Target % of FY' values were generated by smoothing out the months and reducing target percentages for November and May as it was desired to not target lettings in these months as in practice these are serving as backstops. Adjusted and target values are also shown in Table 6.

Table 6. Median Monthly Percentages of Fiscal Year

Month	Median % of FY	Adjusted % of FY	Target % of FY
June	3.5%	3.7%	3.8%
July	0.0%	0.00%	0.0%
August	4.5%	4.6%	7.0%
September	5.9%	6.1%	10.0%
October	11.7%	12.2%	11.0%
November	13.7%	14.3%	11.0%
December	10.5%	10.9%	11.0%
January	12.7%	13.2%	11.9%
February	8.4%	8.8%	10.0%
March	6.9%	7.2%	8.0%
April	5.8%	6.0%	6.3%
May	12.5%	13.0%	10.0%

Adjusted values were used in the optimization for the purpose of generalizing monthly targets as a percentage of the fiscal year to examine how historic years could have operated and target percentages were used to assess outputs for how MoDOT indicated they would like to operate.

Finally, percent difference between award amount and programmed amount was reviewed for non-JOC and non-July projects. By month, with drill downs for paving and bridge projects. Findings are shown in Figure 7 through Figure 9.

- JOC projects have award value equal to programmed amount and zeros can impacted mean and median summary statistics
- July projects have large, skewed values, and the department attempts to only let in July in emergency situations.

The findings show that mean values are almost always higher than the median values. This suggests that the data is skewed by projects that are over the programmed amount by higher margins. Reviewing median percent difference values across all projects shows that only June and April are expected to have award amounts higher than programmed amounts. Further, November and February are the strongest performing months while August and May show bids coming in near the programmed amount.

Results are similar for paving projects, but September and January also perform well, while May and October lettings have performed worse for paving project types. Bridge projects are different in that August performs the best while September, October, April and May struggle to produce beneficial bids. These findings suggest that, when possible, projects should be let between August and March, while paving and bridge projects should be let in November to March. With potentially targeted bridge lettings in August.

Figure 7. Percent Difference by Month - All Projects

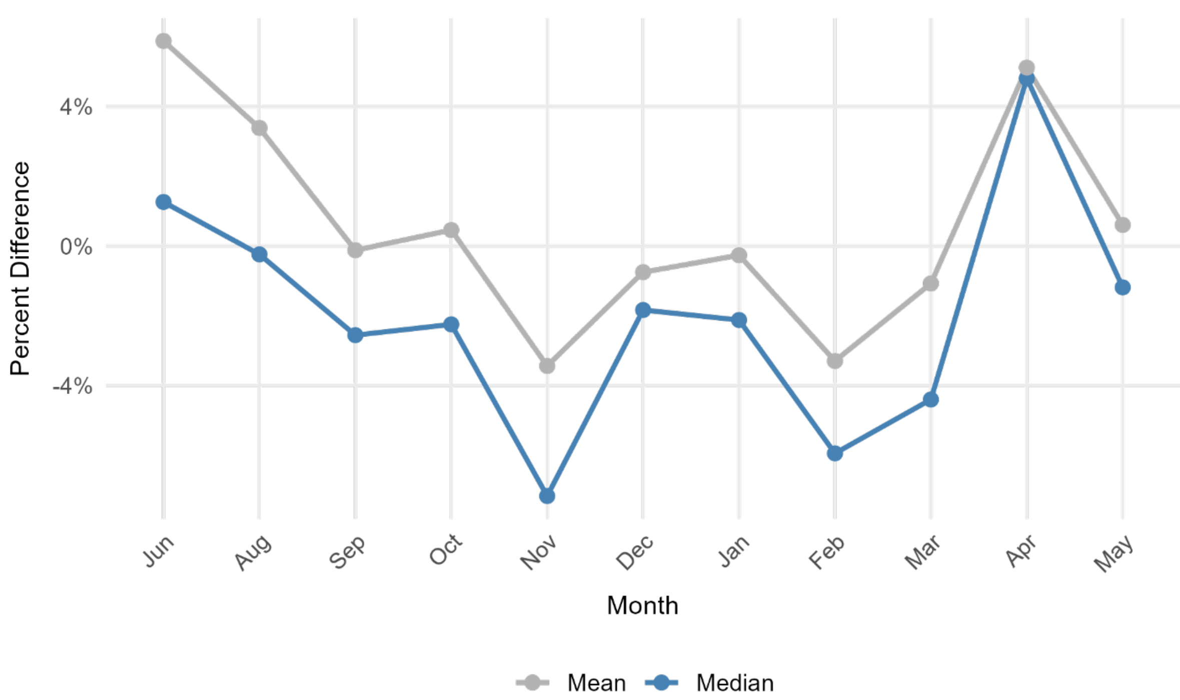


Figure 8. Percent Difference by Month - Paving Projects

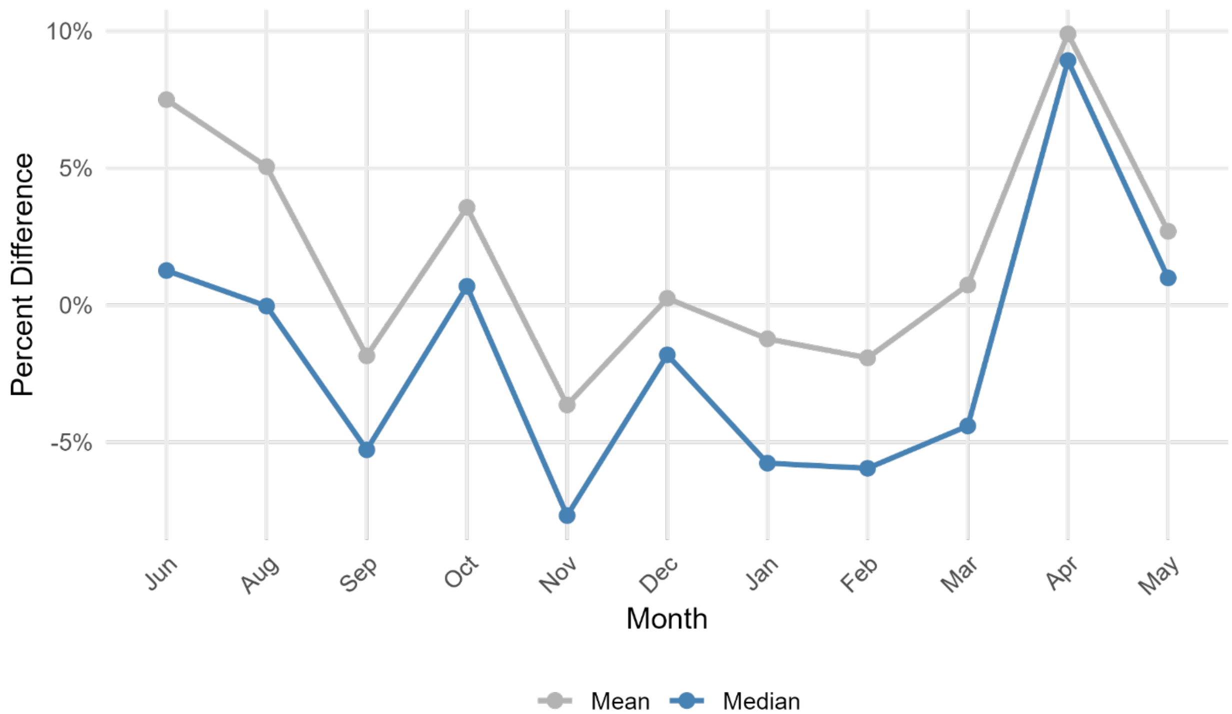
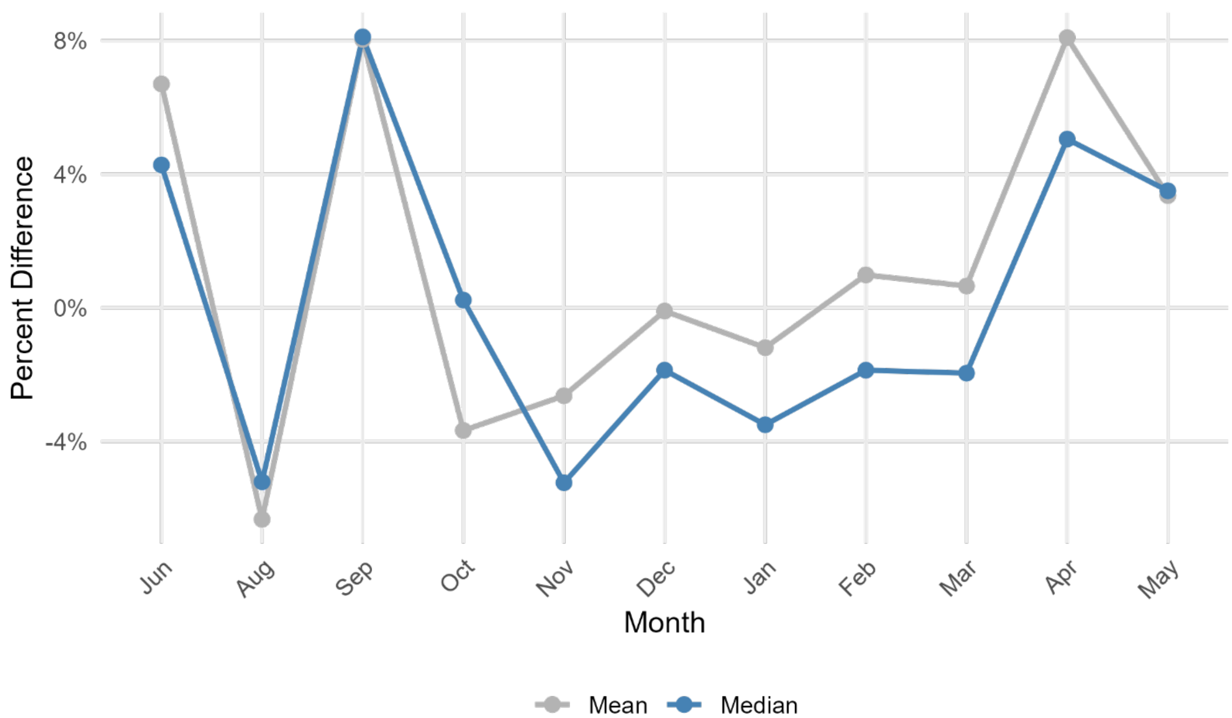


Figure 9. Percent Difference by Month - Bridge Projects



These project types and targeted time frames for best bids can be used in combination with the historical monthly let percentages by project type in constraint development for future optimization.

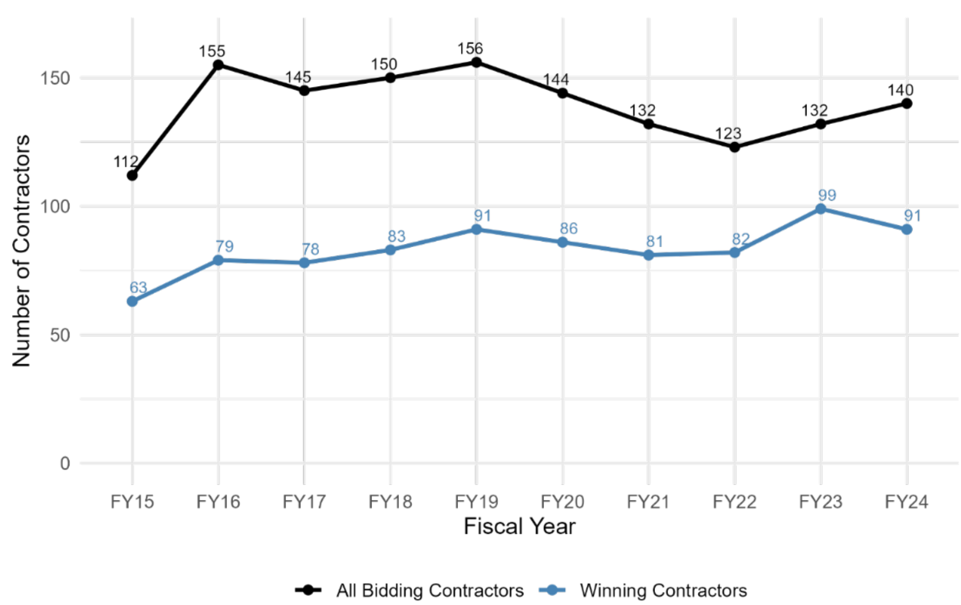
3.3.2. Contractors

This section turns from systemwide historic patterns to the contractors themselves. The goal is to understand how individual firms participate in MoDOT's lettings over time, how much work they are already carrying when new projects are let, and how that existing workload might influence future scheduling decisions. First, contractor activity is profiled over the study period, highlighting how often key firms appear as bidders and winners and how their mix of work has evolved. Next, the prorated backlog measures developed from project start and end dates are used to trace how each contractor's active workload rises and falls month by month, and how those workloads aggregate to a market-level view of capacity pressure. Finally, the section introduces the concept of monthly performance curves. These are simple relationships that translate contractor bidding history into performance by plotting the percent difference most below program to the percent difference highest above program as a function of total letting value.

Historical Bidders

The number of contractors participating in MoDOT lettings has been relatively stable over the past decade. Each year, roughly 140 to 160 unique firms submit at least one bid, with only modest variation from FY 2015 through FY 2024. Within that broader pool, about 60 to 100 contractors win work in a given fiscal year, with a gradual upward drift in the number of winning firms over time (see Figure 10).

Figure 10. Unique Contractor History



This pattern suggests a consistently broad and competitive market. Many firms are active bidders, and a sizeable subset succeeds in securing at least one award each year. The fact that the number of winning contractors has edged up while the total bidder pool remains steady indicates that work is not overly concentrated in a handful of firms, which supports the use of optimization strategies that aim to preserve or enhance competition.

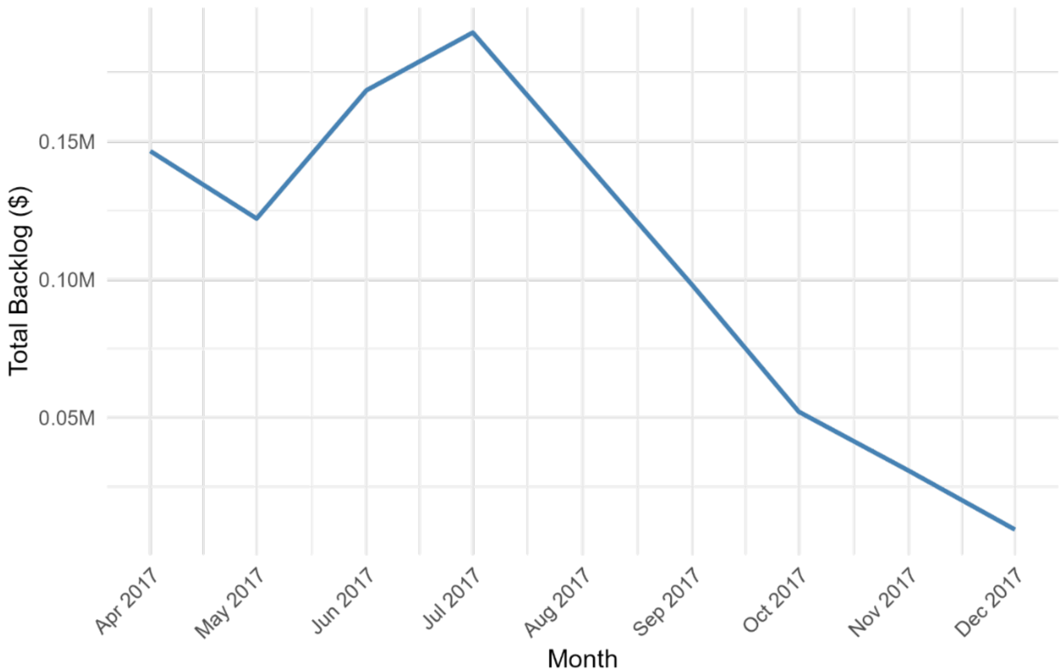
Approximating Contractor Backlog

While actual contractor backlogs are not tracked by MoDOT, the data provided could be used to approximate them. To approximate contractor workload over time, a simple monthly backlog measure was constructed using awarded project data. The starting point was the set of projects with a recorded winning bidder, winning bid amount, and proposed start and end dates. For each project, the winning contractor, the low bid amount, and the proposed start and end dates were used to build a month-by-month profile of remaining contract value.

First, the proposed start and end dates were converted to a sequence of calendar months covering the full proposed duration of the project (for example, from April through September 2020). The total contract value was then assumed to “burn down” at an equal rate over these months. If a project spans N months, the implied monthly spend is the bid value ÷ N. Backlog for that project was defined as the remaining contract value at the start of each month, calculated as the original contract amount minus an integer number of these equal monthly draws. Thus, in the first month the backlog equals the full contract value; in the second month it is reduced by one monthly increment; and so on, until the final active month, after which the backlog drops to zero. This produces a simple, linear burn-down profile that preserves the total contract value while representing backlog of work still under contract.

These project-level backlog profiles were then aggregated by contractor and month. An example of a contractor who won three projects in calendar year 2017 is shown in Figure 11.

Figure 11. Example Contractor Backlog



The above figure shows an approximate backlog for a contractor who had the following project values and start/end dates:

- $147k from April to September
- $71k from June to November
- $57k from July to December

The line starts when the first contract starts, decreases to May, then increases in June and July as new projects start, then burns down through their completion dates

These contractor-month backlogs can be used in simple regressions to test how they influence bid performance and can be aggregated for all contractors to see how market backlog impacts project bid counts.

It should be noted that these curves do not mirror reality precisely. Longer term projects do not account for construction stoppages over winter months. These also take advantage of simplistic linear burn rates when each project and contractor is different, and projects have periods of high burn and other months with minimal burn. MoDOT could further refine these backlog curves by using contractor payment data.

Bid Performance Curves

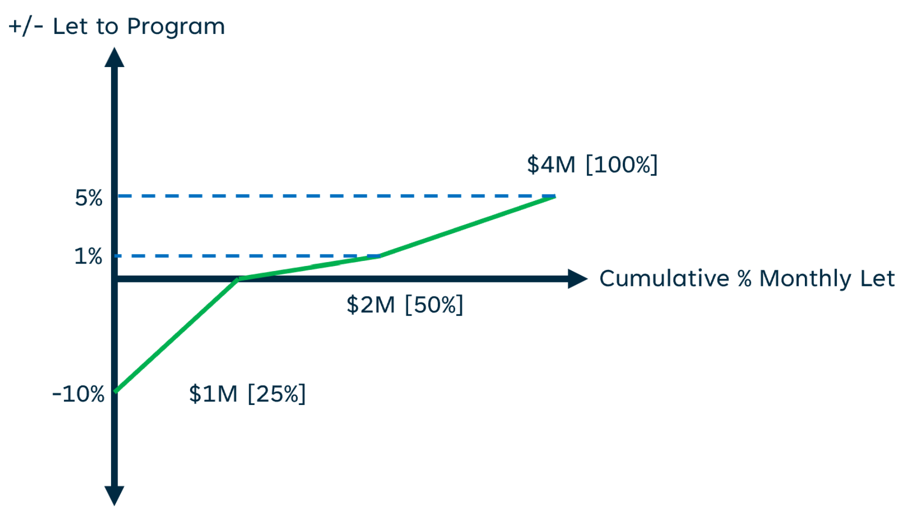
Another method to look at contractor performance, specifically in relation to MoDOT's letting practice and desire to examine how bid performance changes from month to month as more of that month's program was committed. The same data set was used for this exercise (awarded projects, absolute percent difference < 100 percent, no July projects), however JOC projects were excluded. While including them only minimally changes the curves, JOC projects always have a percent difference of zero (e.g. award amount is equal to programmed amount), and do not play a role in later optimization penalty calculations.

For each remaining month-year combination, projects were ordered within the month by their percentage difference, and their programmed amounts were accumulated. A cumulative programmed amount was computed as the running sum of the programmed amount within the month and year, and this was divided by the total programmed amount for that same month–year to produce a cumulative fraction between 0 and 1. This fraction represents the share of that month's programmed dollars that had been committed up to each project in the ordered list. A simple illustrative example is shown in Table 7 and Figure 12.

Table 7. Illustrative Project Data for Building Performance Curves

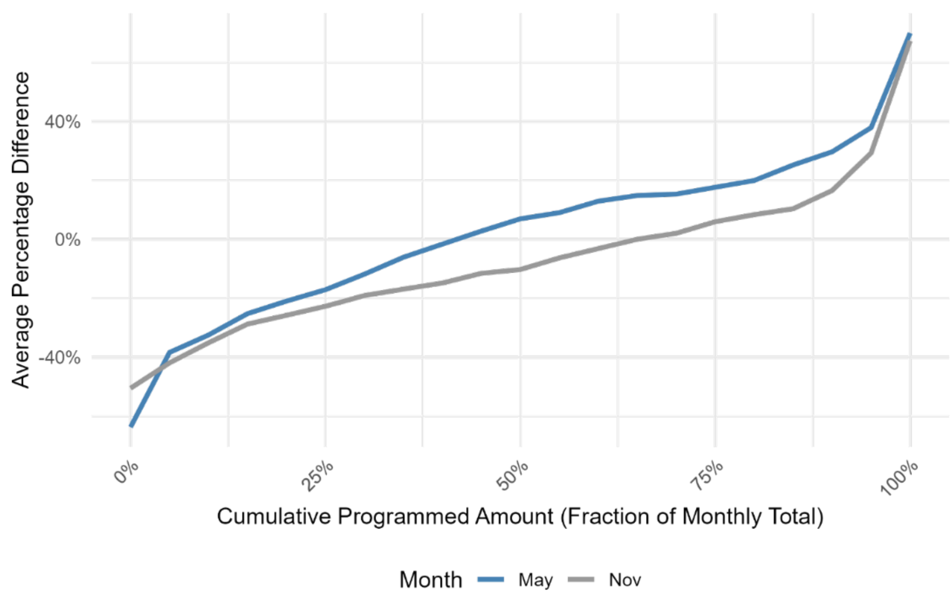
Project	Cost	% Difference	Rank Order	Cumulative %	Cumulative Value
1	$2M	5%	3	100%	$4M
2	$1M	1%	2	50%	$2M
3	$1M	-10%	1	25%	$1M

Figure 12. Illustrative Development of Performance Curve



To obtain smooth, comparable curves with the historical bid data, the relationship between the cumulative fraction and percent difference was interpolated onto a common grid of cumulative fractions (from 0 to 1 in increments of 0.05) for each year using simple linear interpolation where at least two valid points were available. For each month, the interpolated values were then averaged across all years at each cumulative fraction to create an average monthly performance curve showing typical percent difference values as that month's program was progressively committed. Sample curves for November and May developed using FY 2016 to FY 2024 data are shown in Figure 13. Similar curves were developed for all months, and for district/month, and project type/month pairs. The more variables included in the curve development, the rougher the curves become as there become fewer samples the draft the curves from. Some pairs do not have enough data to produce monthly curves. These curves can also be represented as heatmaps and are included in Appendix A. The curves can be used for optimization purposes and the heatmaps can be used as a quick reference for project scheduling if optimization routines are not being utilized. A good way to quickly compare month to month performance is to review the 50th percentile row. Regardless of the variables in the curve, these values typically hover around a zero percent difference (award price near programmed amount).

Figure 13. Performance Curves for May and November



From this graph comparing two of the twelve months it is shown that at the 50 percent cumulative spend point for these months it would be expected for a bid in November to have a -10.2 percent below programmed amount and May to have a value at 7 percent above program. This specific result aligns with commentary from MoDOT of suspected increased bids associated with large May lettings.

While the curves cannot explicitly be used to predict a bid outcome, in aggregate, they can provide an expectation for how bid should perform in a given a specified let month and programmed value for that letting. The curves are generalizable and can be developed for different parameters (e.g., project type, district, or contractor instead of month) and capture the idea that work let in a month for different project types or in a different district perform differently given specific program values. Moreover, these curves can be directly used within an optimization framework to determine what combination of projects in each letting of a fiscal year will produce the best outcomes for MoDOT. One of the primary benefits of these curves is that they ignore confounding variables that arise when trying to explain singular project bid outcomes and capture all of the nuance by including all outcomes.

More about how these curves are used and which optimization scenarios they are used in is provided in Chapter 4. Plots of all performance curves and heatmaps are available in Appendix A.

3.3.3. Project Types

Reduced project types were also reviewed to determine when MoDOT historically lets each project type. For this summary, project costs across all fiscal years were added together within each month by project type. Monthly values were divided by the total historical cost for each project type. Summary percentages are shown in Table 8 through Table 10, higher months are shown in bold.

Table 8. Percent of Bridge Project Program Amount by Month

Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
.04	.01	.05	.05	.07	**.09**	**.08**	**.16**	**.10**	**.10**	**.08**	**.19**

Table 9. Percent of Paving Project Program Amount by Month

Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
.03	.02	.06	**.10**	**.12**	**.19**	**.12**	**.09**	.06	.06	.04	.10

Table 10. Percent of Signing, Striping, Guardrail and Lighting Project Program Amount by Month

Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
.00	.00	.04	.01	.04	.04	.01	.04	**.10**	**.12**	**.18**	**.42**

These tables align with input from MoDOT that they try to let bridge projects from November through February, paving projects between August through January, and signing, striping, guardrail, and lighting projects toward the end of the fiscal year. It was shared that bridge projects are attempted to be intentionally staggered after paving projects, with more flexibility to let during other times of the year. While the historical results differed slightly from MoDOT ideals these values set a historical foundation for when projects are let but can be modified during optimization to test performance with different targets and align with MoDOT letting desires.

3.3.4. Regression

To complement the descriptive charts, a series of simple regression models were estimated to explore how key outcomes vary with project and market characteristics (for example, bid counts, project types, and timing). These models are not intended to fully explain bid outcomes, but rather to highlight relationships that are large enough and consistent enough to be useful inputs for the optimization work in later chapters.

For all regression models, a further refined dataset was produced by joining the award results and bidding data and keeping only complete cases. Categorical variables were converted to factors to support quick hypothesis tests. Statewide projects and projects let in July were removed because each group contained relatively few observations. Extreme outcomes where the winning bid was more than 100 percent above or below the programmed amount were also excluded. These large outliers do occur in practice, but they are rare and can dominate the regression results in ways that are not representative of typical lettings.

Percentage Difference Versus Bid Count.

For the regression analysis, the percentage difference outcome is defined as the percentage difference between the programmed amount and the winning bid amount for each project. Positive values indicate that the winning bid was higher than the programmed amount (i.e., over program), while negative values indicate that the winning bid came in below the programmed amount (i.e., savings relative to program).

As a first step, a simple linear regression was estimated relating percentage difference to the number of bids received:

$$\textit{Percentage difference} = 0.12 - 0.033 \times (\textit{bid count})$$

This model was fit using 3,633 observations. The estimated intercept is 0.12 (standard error 0.01), and the slope on bid count is –0.033 (standard error 0.002). The slope is statistically significant ($t = -13.3$, $p < 0.001$), and the model explains about 4.7 percent of the variation in percentage difference ($R^2 \approx 0.047$, residual standard error ≈ 0.28).

Interpreting the slope, each additional bid is associated with about a 3.3 percent lower percentage difference, meaning that projects with more bidders tend to have winning bids further below the programmed amount. When the bid count is zero (a hypothetical case), the model would predict a percentage difference of approximately +12 percent, indicating bids above program; as the number of bids increases, the expected percentage difference becomes smaller and more negative.

Average Bid Count Versus Project Count

A second regression examined whether the average number of bids per project changes as the total number of projects in a letting group increases. The outcome is the average bid count per project, and the predictor is the project count, representing how many projects are in the same letting. Only lettings with five or more bids were included (e.g. removing emergency, special, and prior July lettings). The median project count per let for this data was 39, and the max project count was 69.

A simple linear regression was estimated of the form:

$$\textit{Average bid count} = 3.69 - 0.0058 \times (\textit{project count})$$

This model was fit using 96 observations. Within this data, the estimated intercept is 3.69 (standard error 0.19), and the slope on project count is –0.0058 (standard error 0.0048). The slope is not statistically significant ($t = -1.21$, $p = 0.23$), and the model explains only about 1.5 percent of the variation in average bid counts ($R^2 \approx 0.02$; residual standard error ≈ 0.68).

Interpreting the slope, the point estimate suggests that adding more projects to a letting group is associated with a very small reduction in average bids per project (about 0.006 fewer bids for each additional project), but this effect is both statistically insignificant and practically negligible. Within the range of observed data, variation in the number of projects per period does not appear to be a meaningful driver of bidder participation compared with other factors.

Bid Count Versus Month, Project Type, and District

A multivariable regression was estimated to examine how bid counts vary with timing, project size, location, and project type. The outcome is the number of bids per project. Predictors include month of letting, contract type (e.g. regular, JOC, or other), the programmed amount, district, fiscal year, and a simplified project type indicator.

In simplified form, the model can be written as:

Bid count = 4.22 +

- *adjustments for month of letting*
- *adjustments for JOC status*
- *0.02 × log(programmed amount)*
- *adjustments for district*
- *adjustments for fiscal year*
- *adjustments for project type.*

The model uses the same 3,633 filtered observations as the earlier regression. The intercept is 4.22 (standard error 0.39). Several predictors are statistically significant:

- *Month of letting.* Relative to June, August through November receive more bids, while December through April receive less bids. However, August and September are the only statistically significant months associated with slightly higher bid counts than June month, with coefficients of +0.34 ($p \approx 0.07$) and +0.41 ($p \approx 0.02$), respectively. Other months are not statistically different from the reference month.
- *JOC status.* JOC contracts receive fewer bids. The coefficient for JOC is –1.38 (standard error 0.11, $p < 0.001$), indicating roughly 1.4 fewer bids than comparable non-JOC projects.

- *District.* Several districts have higher bid counts than the Northwest District, with coefficients ranging from about +0.23 to +0.66 bids (all $p < 0.05$). This suggests that local market conditions and contractor presence by district are significant.
- *Fiscal year.* Controlling for other factors, later years show lower bid counts than the reference year. For example, FY20 has –0.52 bids, FY22 has –0.94 bids, FY23 has –1.20 bids, and FY24 has –0.78 bids (all $p < 0.001$), indicating a downward shift in bidder participation over time. This aligns with results in Figure 3.
- *Project type*. Relative to the bridge project-type category, "Other," "Paving," "Signals," and "SSGL" projects all have significantly fewer bids, with coefficients between about – 0.85 and –1.76 (all $p < 0.001$). These project types tend to draw 1–2 fewer bids than the bridge category. This indicates that there is more competition for bridge projects than other project types.
- *Programmed amount.* Programmed amount itself is not statistically significant once these other factors are included.

Overall, the model explains about 24.6 percent of the variation in bid counts ($R^2 = 0.246$; residual standard error ≈ 1.63), indicating that timing, location, contract type, and simplified project type together capture a meaningful share of the systematic differences in bidder participation.

Percentage Difference Versus Contractor Backlog

This regression tests whether a contractor's active backlog in the month of letting is associated with the percentage difference between the programmed amount and the winning bid. The outcome is percent difference (defined earlier as the percentage difference between programmed and winning bid), and the predictor is the prorated backlog (as developed in the Contractors section above) for that contractor in that month (in dollars).

A simple linear regression was estimated of the form:

$$\textit{Percentage difference} = 0.022 + 0.000000002 \times (\textit{contractor backlog in dollars})$$

This model was fit using 3,704 observations. The estimated intercept is 0.022 (standard error 0.009; $p = 0.016$), and the slope on backlog is 0.000000002 (1.998×10^{-9}, standard error 3.89×10^{-10}; $t = 5.13$; $p < 0.001$). The model explains about 0.7 percent of the variation in percentage difference ($R^2 \approx 0.007$; residual standard error ≈ 0.48).

Interpreting the slope, higher contractor backlog is associated with slightly higher winning bids relative to programmed amounts. An additional $1 million in backlog is associated with an increase of about 0.002 percent (roughly 0.2 percentage points higher). An additional $10 million of backlog corresponds to an increase of about 0.02 (roughly 2 percentage points), and $50 million corresponds to about 0.10 (roughly 10 percentage points). While the relationship is statistically detectable in this large dataset, contractor backlog by itself accounts for only a small share of the overall variation in how bids compare to programmed amounts.

Bid Count Versus Contractor Backlog

This regression looks at whether overall market backlog in each month is associated with the number of bids received per project. The outcome is project bid count, and the predictor is total market backlog, the sum of prorated backlog across all contractors in that month (in dollars).

A simple linear regression was estimated of the form:

$$\textit{Bid count} = 4.18 - 1.51 \times 10^{-9} \times (\textit{market backlog in dollars})$$

The model was fit using 3,704 observations. The estimated intercept is 4.18 (standard error 0.07), and the slope on total backlog is -1.51×10^{-9} (standard error 1.34×10^{-10}; $t = -11.28$; $p < 0.001$). The model explains about 3.3 percent of the variation in bid counts ($R^2 \approx 0.033$; residual standard error ≈ 1.84).

Interpreting the slope, higher overall backlog in the market is associated with slightly fewer bids per project. An additional $100 million in market backlog is associated with about 0.15 fewer bids on average, and $1 billion backlog is associated with about 1.5 fewer bids. For reference, the market backlog has data characteristics:

Table 11. Backlog Summary Statistics

Summary Statistic	Value
25th Percentile	$318M
Median	$440M
Mean	$481M
75th Percentile	$652M
Max	$998M

The effect is statistically detectable and directionally consistent with the idea that very busy markets draw fewer bidders to each project, but market backlog alone explains only a small share of the total variation in bidder participation.

3.3.5. Variable Importance

In addition to the linear regressions, a simple machine-learning model was used to check which factors are most influential in explaining variation in bid outcomes. A random forest model with 5-fold cross-validation was fit using the same regression dataset, allowing for nonlinear relationships and interactions among variables without imposing a specific functional form.

The primary purpose of this exercise is not prediction, but prioritization, and identify which variables consistently have the largest influence on bid count and the percentage difference between programmed amounts and winning bids. Variable importance plots are shown in Figure 14 for bid count and Figure 15 for percentage difference.

Figure 14. Bid Count Variable Importance

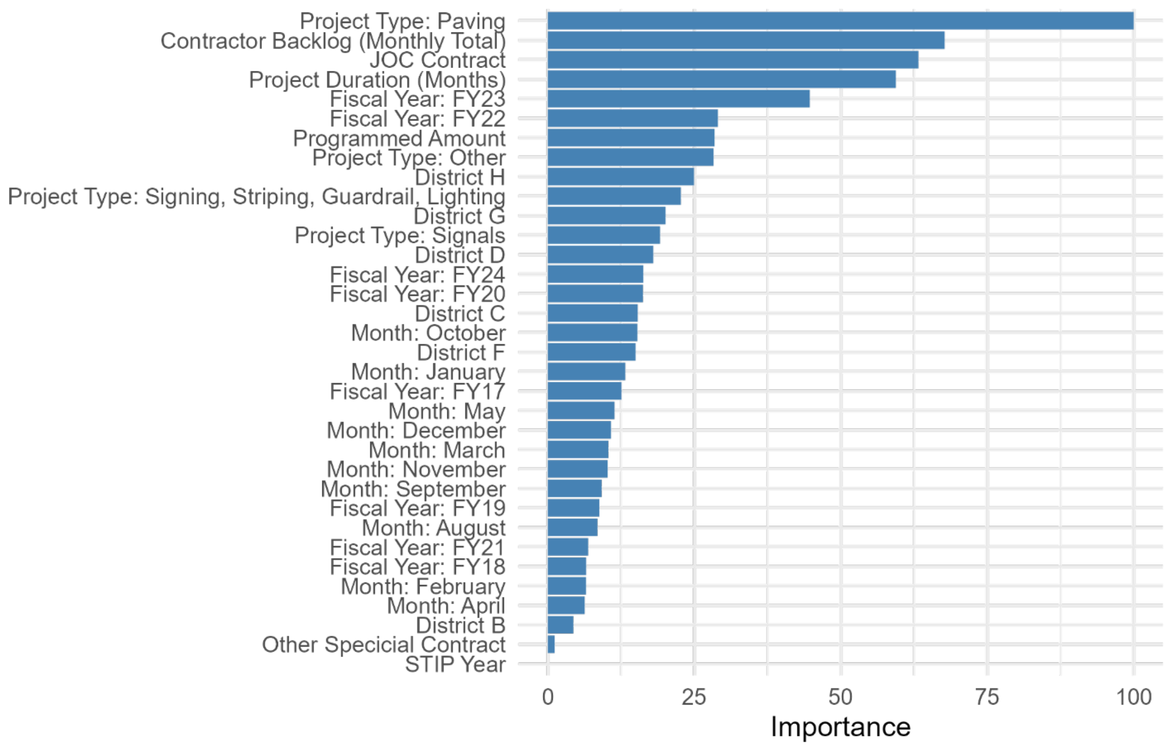
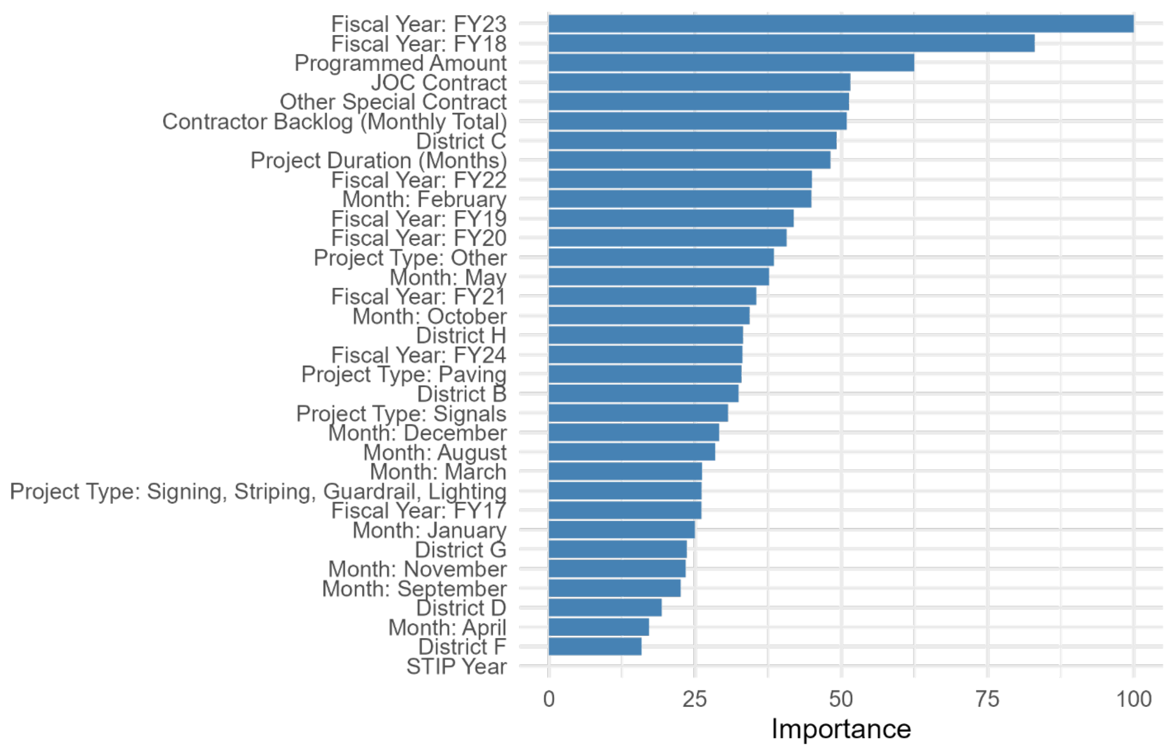


Figure 15. Percent Difference Variable Importance



The two variable-importance charts tell a consistent story about what matters for MoDOT's lettings, but with some nuance between bidder participation and pricing. For bid count, the signal is very concentrated, where Project Type: Paving and Contractor Backlog (Monthly Total) are clear standouts, followed by JOC contracts, project duration, and a few fiscal-year and district effects. That pattern suggests that "what the job is" and "how busy the contractors are" are the primary levers for how many bidders show up, with timing and location playing secondary but still meaningful roles.

For percent difference, importance is spread more evenly across a broader set of variables. Fiscal year, programmed amount, JOC and other special contracts, backlog, and month indicators all carry substantial weight, with project type and district still contributing but not dominating. This flatter profile is consistent with pricing being a more multi-factor outcome. Small contributions from timing, contract form, project type, and market conditions all add up.

In short, bid counts are driven most strongly by project type and contractor workload, while percent difference depends on a wider mix of timing, contract, and program-size factors, which is exactly how the optimization work should treat them.

3.4. Exploratory Analysis Conclusions

The data assembly, exploratory diagnostics, and preliminary modeling work established a practical foundation for letting optimization and policy design. The following points were demonstrated and are positioned for direct use in optimization or translation into implementable practice:

- Usable analysis universe was established. A unified FY2016 – FY2024 dataset was constructed from MoDOT bid openings, full bid tabs, and letting results. Non-comparable procurements were excluded, bundles were identified by call number, and project types were standardized into five analysis groups. This standardized baseline enabled consistent measurement of bidder counts and pricing relative to programmed amounts. The data format also allows for future year STIPs to be ingested into optimization algorithms.
- Programmed amounts served as the pricing benchmark. In the absence of engineer's estimates, percent difference from program was employed consistently. This measure was shown suitable for comparative analysis across months, districts, and project types and was adopted for optimization objective/penalty construction.
- Timing effects were material and operationally relevant. Month letting patterns were documented for project counts and dollars, including recurring concentration in late fall and May. These patterns were used to derive monthly target shares of the fiscal program, providing implementable monthly targets that can be encoded as constraints or soft penalties in optimization.
- Competition varied with contract form and context. Bidder participation was observed to differ by JOC status (fewer bids), by simplified project type, and by district. These

effects were incorporated as guardrails (e.g., separate handling of JOCs, minimum-competition thresholds, and district level balancing) rather than treated as noise.

- Contractor workload proxies supported congestion management. A transparent backlog approximation, spreading awarded values between proposed start and end date was developed to track monthly active work by firm and for the market. Although simplified, this proxy could enable workload-aware outcomes, and was tested via Monte Carlo simulation, described in Chapter 4.
- Performance curves were derived for use in optimization. Month specific curves relating cumulative monthly program share to expected percent difference were produced. These curves provided an empirically grounded way to score monthly letting packages and to penalize over concentration, directly informing the optimization objective.
- Monitor market and firm backlog and adjust advertising cadence when workload is elevated or target contractors are reaching capacity. Backlog monitoring could be changed from an approximation to actual backlog and production rates using pay item receipts.
- Data limitations were acknowledged and made actionable. Known gaps (geocoded locations, pit/plant proximity, ROW/environmental/utility readiness indicators, engineer's estimates, and neighboring state schedules) were documented and translated into data-collection recommendations to strengthen future schedule design and tracking.

In sum, an analysis ready dataset was created, empirically meaningful drivers of competition and pricing were prioritized, and directly implementable rules and penalty functions were prepared. These elements were then positioned to inform optimization scenarios and near-term policy adjustments aimed at smoothing lettings, protecting competition, and preserving purchasing power in MoDOT's STIP.

4. Optimization Analysis

This chapter introduced a practical optimization of MoDOT's letting calendar grounded in the empirical patterns from Chapter 3. A schedule was sought that reduced expected award costs while respecting real-world constraints. The methods section described how an optimization algorithm was configured, what data informed it, and how operational constraints were encoded. Scenario design was then outlined to test specific levers and targets. Monte Carlo sensitivity runs were used to assess robustness to uncertainty in the performance curves and parameter choices. Results were summarized at program and month levels, and the chapter closes with key findings and takeaways that translate directly into schedule guidance.

4.1. Optimization Methods

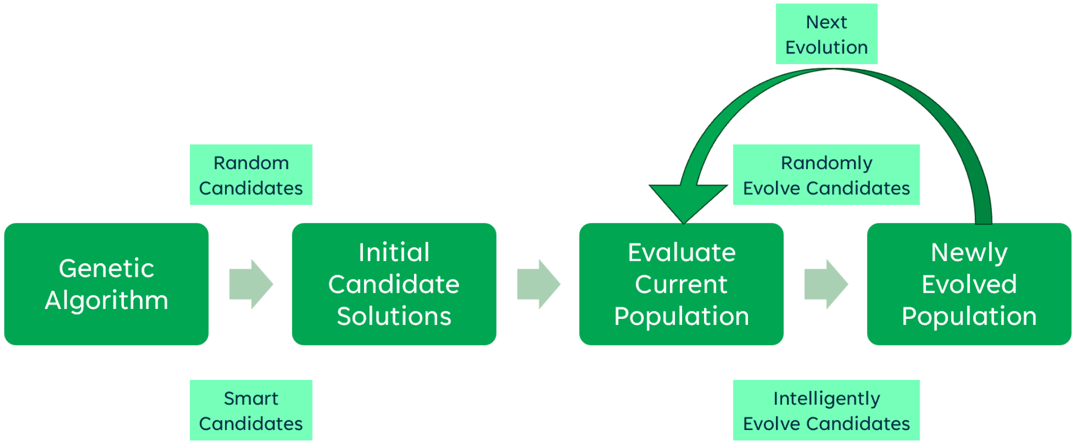
4.1.1. Algorithm Selection and Process

Optimizing the assignment of 400+ construction projects to monthly letting periods presents a combinatorial challenge that defies traditional optimization approaches. The search space, potentially 11^400+ configurations, is far too vast for exhaustive methods. Given the discrete nature of project assignments and the complex non-linear multi-objective fitness function, this rules out gradient-based techniques. While Integer Linear Programming (ILP) approaches were considered, the complexity and nonlinearity of our real-world constraints make ILP formulations impractical and risk significant loss of model fidelity. Moreover, the huge number of variables and rules needed to encode every eligibility and interaction would make the ILP practically unsolvable for this problem size. Lastly ILP would be far more brittle and difficult to adjust as the optimization needs adapt and expand.

Genetic algorithms (GA) offer an elegant solution to this problem. They naturally represent complete letting schedules as chromosomes, efficiently explore rugged fitness landscapes through population-based search. Also, they gracefully handle both hard constraints (such as seasonal eligibility and excluding July) and soft constraints (such as district balancing) through mutation operators and penalty functions. Furthermore, project bundling (calls), where multiple projects are grouped and must be scheduled together, was easily accommodated by simply encoding bundling relationships in the chromosome structure and constraint enforcement logic, without complicating the optimization process. Combined with Monte Carlo simulation for uncertainty quantification, this approach delivers practical, interpretable schedules while remaining computationally tractable.

In addition, the genetic algorithm approach supported auditability and extension. New business rules could be introduced as additional feasibility checks or penalty terms without rederiving coding infrastructure. Scenario variants were produced by toggling constraint modules and weights, while the same fitness evaluations were retained. This flexibility, combined with stable performance under sensitivity tests, made the genetic algorithm an appropriate and defensible choice for translating empirical relationships into implementable letting schedules. The general genetic algorithm workflow is shown in Figure 16. Savings were achieved by reducing expected bid amounts through scheduling projects in months when bids had historically been lower, and by shifting work away from lettings associated with higher prices, all while honoring relevant constraints.

Figure 16. Genetic Algorithm Workflow



The problem was framed with 11 monthly letting buckets and roughly 400 projects depending on the specific FY. For each project, a feasible month was assigned under the letting rules, and a projected bid amount was computed by applying the month's base discount or penalty and an additional congestion adjustment that depended on how full the month already was. Projected bid amounts were then totaled within each month and across the program.

4.1.1.1. How Evolution Works: A Concrete Example

To illustrate how the genetic algorithm improves letting schedules, consider a single evolution step for one project. Each letting month has an associated bid multiplier that reflects contractor capacity utilization. Months with more available capacity have lower multipliers (discounts), while congested months have higher multipliers (penalties). These are effectively our penalty curves.

Starting State

Consider *Project 1* with a program amount of $100 currently assigned to May. May is a congested letting month with a bid multiplier of 1.10 for *Project 1*, so the predicted bid and starting point for our evolution is:

Predicted May Bid = $100 x 1.10 = $110.

Random Evolution

The random mutator selects a project at random and moves it to a randomly chosen eligible month. In this case, suppose it moves *Project 1* from May to April. April has slightly less congestion with a bid multiplier of 1.05 for Project 1:

Predicted Evolved to April Bid = $100 x 1.05 = $105

This is a $5 improvement (4.5 percent reduction). The random mutator found this by chance, meaning it didn't analyze which month would be best, it simply tried a valid move. Sometimes random mutations make things worse, but over many generations, beneficial mutations accumulate while harmful ones are selected against.

Intelligent Evolution

The intelligent mutator takes a more strategic approach. Before moving a project, it scans the eligible months to identify which ones have available capacity and favorable multipliers.
For *Project 1*, the intelligent mutator identifies that October has significant room and a bid multiplier of only 0.90 (a 10 percent discount due to low contractor utilization):

Predicted Evolved to October Bid = $100 x 0.90 = $90

This is a $20 improvement (18 percent reduction) compared to the original May assignment, and $15 better than the random mutator's April move.

Why Both Approaches Matter

You might wonder: why use random mutations at all if intelligent ones are better?

The answer lies in Exploration vs. Exploitation and computational speed.

Intelligent mutators exploit known good opportunities but can miss unexpected solutions. They follow local gradients and may converge to local optima. Also, intelligent mutation is computationally expensive, so those must be used more sparingly. Random mutators explore the broader search space. A seemingly bad move might enable a cascade of improvements in subsequent generations or might find regions of the solution space the intelligent mutator would never consider.

By combining both strategies, the GA benefits from rapid improvement (intelligent moves) while maintaining diversity and avoiding premature convergence (random moves). In practice, multiple mutators are often run in parallel, some moving 1 project, others moving 2, 3, or 5 projects simultaneously to balance fine-tuning with larger exploratory jumps.

4.1.1.2. How Performance Curves and Penalty Functions Work in Optimization

Scoring a monthly letting solution for a FY relied on month-specific performance (penalty) curves. For each month, programmed dollars assigned to that month were mapped to the curve to obtain a projected percent difference and implied bid amount. When monthly assignments exceeded 100 percent of the month’s historical program share, the curve was extended horizontally to impose the maximum penalty for project placement over 100 percent.

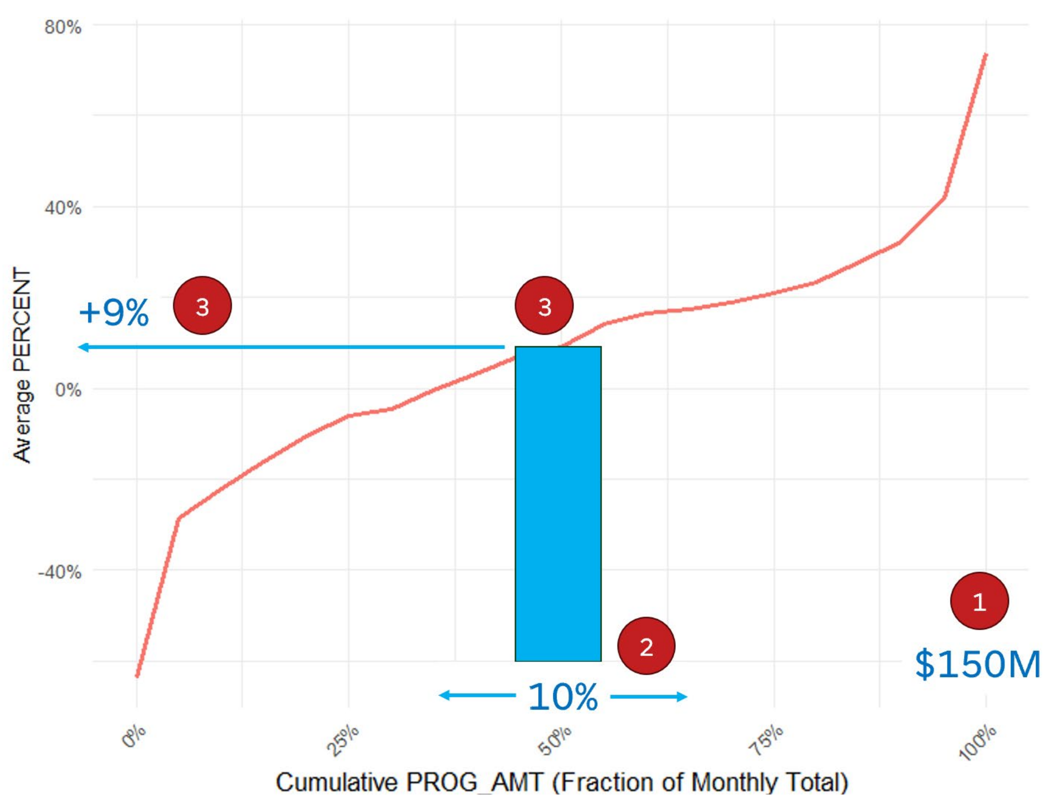
To demonstrate how the performance function works, an illustrative example is used. For this example, assume:

- A FY budget of $1B
- 15 percent of that annual budget goes to the month of May
- The first project assigned to a monthly bucket is $15M and is randomly assigned to May

The steps for assigning a probable cost are outlined below and are shown in Figure 17 for this example project are:

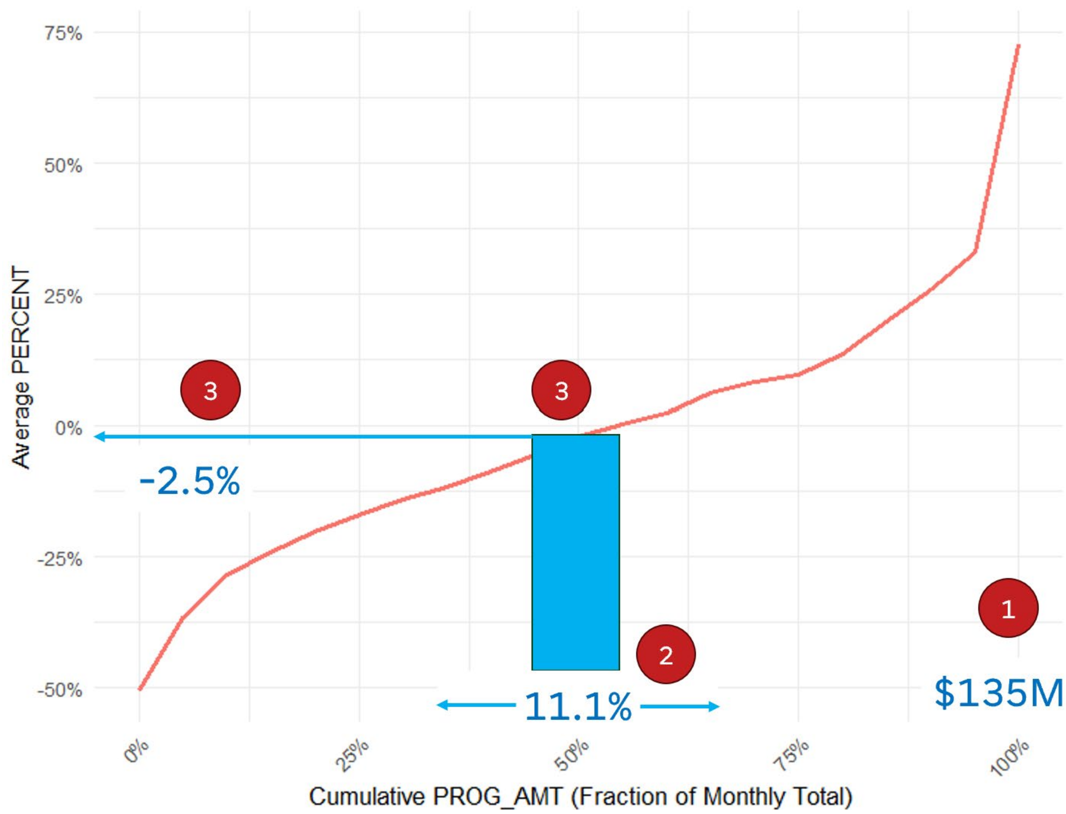
1.) Determine the 100 percent value for the cumulative total value in May. In this case that value is .15 * $1B, or $150M.
2.) Assign the project to the middle of the curve. In this instance, the example project accounts for $15M / $150M = 10 percent of the cumulative monthly budget.
3.) A line is drawn vertically from the project width until the middle of it reaches the performance curve. Then a line is drawn horizontally to obtain the performance assigned to the project.
4.) Repeat to assign all projects across all monthly lettings working from the middle of the curve to the edges.
5.) We start with the largest projects first, placing them towards the middle and the smaller projects get put towards the left/right sides. This is because historically, large projects neither get big discounts or penalties, those extremes are reserved for smaller projects.

Figure 17. Performance Function Demonstration - May



An additional example is shown in Figure 18 to demonstrate how changing the monthly letting impacts estimated project bid performance.

Figure 18. Performance Curve Demonstration - November



These images show that letting the sample $15M project in May would result in a project cost of approximately $16.4M while letting the same project in November would only cost approximately $14.6M.

4.1.1.3. Why is using performance curves effective to optimize projects?

Performance curves were effective because they are derived from observed letting outcomes across a substantial multi-year sample, which grounded the optimization in demonstrated market behavior. The curves implicitly captured contractor bidding responses as a function of capacity by linking expected prices to the cumulative share of monthly program value. Other explicit procedural nuances in letting practice were intentionally abstracted to retain a tractable, data-driven signal. The approach is also generalizable. That is, historical periods judged atypical can be excluded, fluctuating program sizes can be accommodated, and the underlying data structure was sufficiently generic to be applied by any DOT.

4.1.1.4. Optimization Constraints

The optimization algorithm builds upon empirical findings in Chapter 3 and used input from MoDOT to refine when and how projects should be let, specifically, the following constraints were used:

- Projects cannot be let in July
- A project cannot be moved to a letting in the same month as, or after its start date.
- A project identified as part of a call package (bundle) will be moved to a letting month with all other projects in that call package.
- Monthly percent of FY targets are based on median values of historic fiscal years and are shown in Table 12.

Table 12. Target Monthly Optimization Values

Month	Target (Median Historical Values)
Jun	3.7%
Jul	0.00%
Aug	4.6%
Sept	6.1%
Oct	12.2%
Nov	14.3%
Dec	10.9%
Jan	13.2%
Feb	8.8%
Mar	7.2%
Apr	6.0%
May	13.0%

- JOC projects are included in the summation of total monthly value but are not assigned a performance. Estimated let value is always equal to historical programmed amount.
- Districts are not to let more than 30 percent of their FY program in a single month. This is a soft constraint, which means the optimizer allows it to be broken, but places a fairly steep additional cost. So, for instance, in one running of the optimization for FY22, early generations have an optimized let around $980M, but the various penalties cause that to go up to $15B with penalty, which is what is optimized against. Within a few generations the penalties go down significantly to where the penalty factor almost completely disappears by the end.
- A proportion of the total of each of paving, bridge, and signing, striping, guard rail and lighting type projects, and projects that are considered ‘large’ are targeted to be let in certain months. Large projects are those over $10M. Large project value and target percentages are based on historical analysis outlined in Chapter 3 and based on input from MoDOT. These constraints are shown in Table 13.

Table 13. Project Type Constraints

Month	Bridge	Paving	Large	Striping
Jun				
Jul				
Aug		10%		
Sep		10%		
Oct		10%	20%	
Nov	10%	10%	20%	
Dec	10%	10%	20%	
Jan	10%	10%	20%	
Feb	10%			20%
Mar	10%			20%
Apr	10%			20%
May				20%

Constraints reflected a combination of observed practice, historical data, and input from MoDOT and were encoded as soft caps unless noted. These constraints were used in various combinations as highlighted in the scenario section below. Project schedules were distributed across the remaining eleven monthly buckets.

4.2. Scenario Design

A suite of scenarios was specified to test policy-relevant levers and alternative targets. These included:

Historical Baseline. Actual letting month assignments and realized low bids were summarized for context.

Monthly Distribution (Base). Projects were optimized across months to minimize projected low bids using only the month performance curves and historical median monthly targets. This is the “Base” scenario.

Equal Monthly Distribution. Projects were optimized across months to minimize projected low bids using only the month performance curves and uniform 1/11 share per month targets to smooth dollars across the year.

Monthly Distribution + Districts. Same as the monthly distribution scenario with additional soft constraint for districts to not exceed more than 30 percent of FY program in a single month.

Monthly Distribution + Bridge. Same as the monthly distribution scenario with additional soft constraint for bridge projects to target at least 10 percent or more per month during the months of November through March to target typical historical letting months and where award performance is the best, while still providing flexibility for bridges to be let in other months.

Monthly Distribution + Paving. Same as the monthly distribution scenario with additional soft constraint for paving projects to target at least 10 percent or more per month during the months of August through January to target typical historical letting months and where award performance is the best, while still providing flexibility for paving projects to be let in other months.

Monthly Distribution + SSGL. Same as the monthly distribution scenario with additional soft constraint for SSGL projects to target at least 20 percent or more per month during the months of February through May to target typical historical letting months and allow for prioritization of more expensive paving and bridge projects in the better performing fall and winter months.

Monthly Distribution + Paving + Bridge + SSGL + District (All). Combination of all constraints including in the prior four scenarios to constrain when districts, paving, bridge, and SSGL projects are let.

Base – Large Projects: Used Base scenario constraints but removing the “large projects first” operation. This allowed larger projects to start at the higher and lower ends of the performance curve.

Base Bridge Sensitivity Tests. Used Base scenario constraints but adjusted bridge timing to target with 15 percent or more of projects in November through February.

Base with New Monthly Target Distribution. Used Base scenario constraints but applied new target monthly distributions as shown in Table 14. These modified targets were developed based on input from MoDOT as to try not to target larger lettings in November and May as they are FY year end months for the federal and state calendar and projects that slip often land in these months.

Table 14. Ideal Monthly Target Distribution

Month	Target percent
Jun	3.8%
Jul	0.0%
Aug	7.0%
Sep	10.0%
Oct	11.0%
Nov	11.0%
Dec	11.0%
Jan	11.9%
Feb	10.0%
Mar	8.0%
Apr	6.3%
May	10.0%

District + Project Type Distributions. Instead of using the monthly performance curves, new curves were developed using the same methodology for month + district and month + project type pairs. Projects were assigned for months and expected costs were calculated using both curves and were then averaged. These two curves now determine our overall penalty. The purpose of this scenario was to try and provide more nuance to bid performance based on the pairing of district and project type, with the underlying hypothesis that that the contractor segments within each of these pairs act differently. There are three methods used for determining the penalty for a project let in each month:

- Obtain how full the month is overall as a share of its total dollars. Use that same "how full is the month" position to read both the district curve and the project-type curve. Take the average of those two penalties.
- Obtain how full the month is for that district specifically and get the district penalty. Separately, look at how full the month is for that project type specifically and get the project type penalty. Average the two penalties.
- Same as the first, but instead of averaging the district and type penalties, take the larger one. This treats the tighter of the two as the limiting factor.

This more nuanced approach was researched to see how it differed from base scenarios. These scenarios were run on FY 2016 through FY 2024. District and project type targets for this scenario are in Table 15 and Table 16 below.

Table 15. District Monthly Targets

	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
Northwest	14.1%	16.9%	8.7%	8.5%	15.6%	6.4%	8.1%	5.8%	5.9%	7.0%	3.0%
Northeast	3.9%	4.8%	4.8%	11.9%	15.8%	21.7%	14.2%	6.0%	7.7%	4.2%	5.1%
Kansas City	4.1%	7.3%	4.0%	9.4%	15.4%	10.8%	17.4%	7.0%	5.8%	4.3%	14.6%
Central	1.9%	2.1%	13.6%	14.9%	21.8%	10.9%	10.2%	7.8%	4.0%	5.0%	7.8%
St. Louis	2.3%	1.3%	3.8%	9.2%	9.2%	10.8%	12.0%	9.7%	8.1%	7.6%	26.1%
Southwest	1.3%	4.4%	13.7%	10.2%	16.9%	3.6%	8.3%	9.6%	8.8%	8.5%	14.6%
Southeast	2.7%	1.7%	2.9%	11.9%	13.1%	10.8%	12.1%	11.0%	15.2%	5.6%	13.0%

Table 16. Project Type Monthly Targets

	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
Paving	3.4%	5.2%	10.4%	11.0%	20.4%	11.8%	10.2%	7.2%	6.1%	3.7%	10.6%
Bridge	3.8%	5.4%	4.4%	6.3%	8.4%	8.1%	16.7%	9.9%	10.4%	7.5%	19.0%
SSGL	0.0%	2.1%	0.9%	4.9%	4.2%	0.9%	3.0%	15.1%	8.1%	15.4%	45.4%
Signals	2.4%	5.9%	5.4%	0.4%	0.3%	10.6%	14.7%	5.2%	17.5%	8.4%	29.2%
Other	3.5%	3.3%	4.5%	12.2%	8.3%	11.1%	11.7%	11.3%	8.3%	10.1%	15.7%

4.3. Monte Carlo Sensitivity Testing

Given uncertainty in the optimization outcomes, a series of Monte Carlo tests were conducted to assess the range of outcomes and assess validity of methodology, assumptions, and constraints. Together, the Monte Carlo experiments provided a credible envelope of variability around the optimization results. Likely ranges for annual and month-level outcomes were quantified, sensitivity to key assumptions was exposed, and failure modes (e.g., capacity congestion or readiness slippage) were stress-tested. As a result, the expected direction and magnitude of savings were corroborated, and practical expectations were set for year-to-year performance under real-world uncertainty.

Monte Carlo sensitivity tests were conducted on optimization solutions and the following scenarios were used:

4.3.1. Within Month Reordering

Projects were permuted within a month and re-mapped along the month curve to reflect alternative commitment sequences. The result of the reordering were projects equally across the distribution from 0 to 100 percent of the performance curve and variance around the optimized result was tight. The simulation was repeated 1,000 times to create a range of expected variability of optimization results.

4.3.2. Curve Placement Uncertainty

Projects were allowed to land anywhere along the month curve to represent dispersion around expected positions. Under this simulation, while unlikely, it would be possible for all projects in a month to land at the high or low end of the performance curve. The simulation was repeated

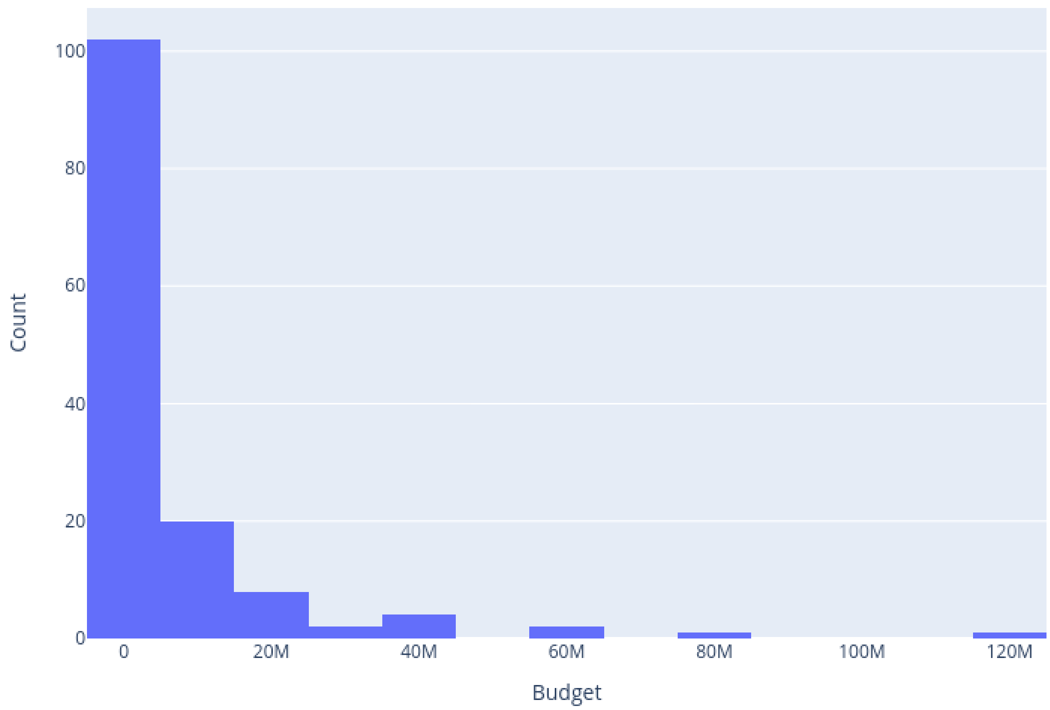
1,000 times to create a range of expected variability of optimization results. This resulted in a larger variance around optimized total program values.

4.3.3. Contractor Backlog Curve Probabilistic Bidding

A Monte Carlo procedure was specified to evaluate how capacity pressures could influence bidding outcomes under the proposed monthly schedules. For this simulation, it was assumed that each contractor possessed a baseline annual capacity and that bid aggressiveness varied with the share of that capacity already committed.

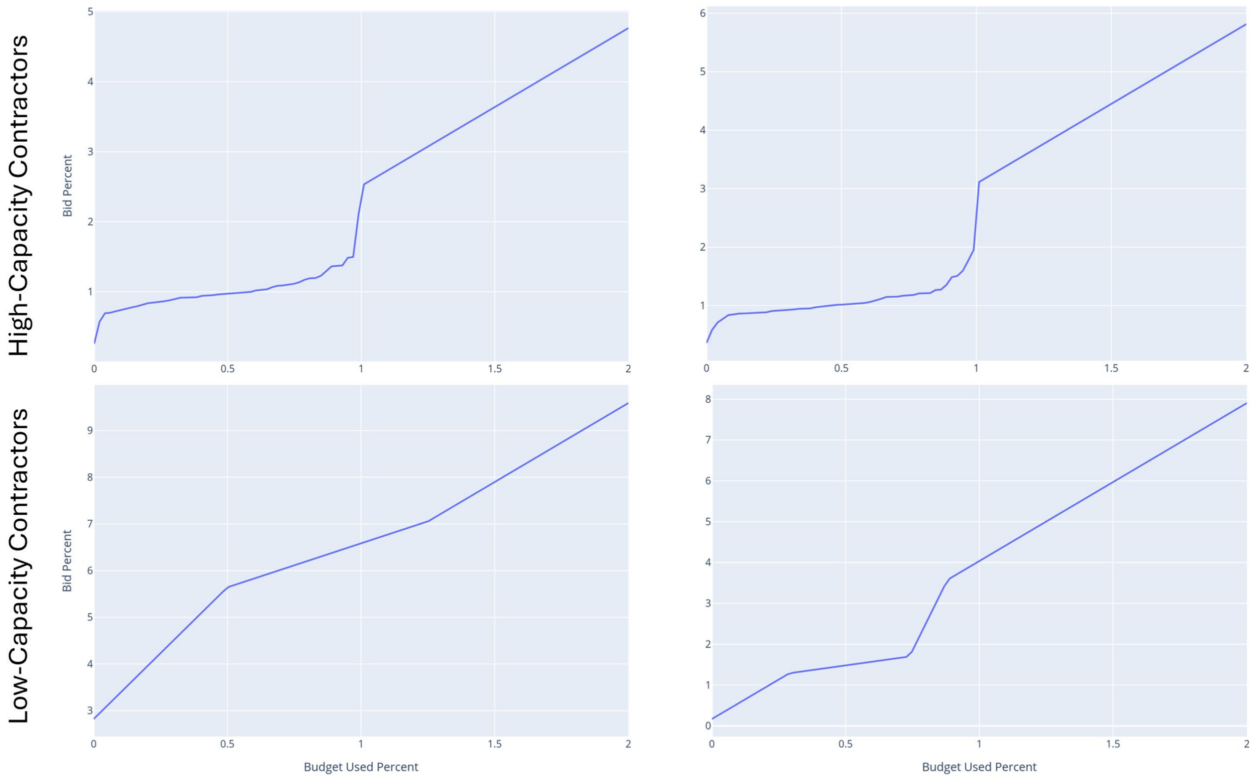
First, the contractor pool was defined as firms with at least one winning bid since FY 2019 (140 unique contractors). For each firm, baseline capacity was estimated as the 67th percentile of total dollars won across fiscal years. This percentile was chosen by researching the behavior of the model when the budget was at 50th percentile, 67th and 75th, and comparing performance with other Monte Carlo simulation and optimization results. A histogram of the estimated contractor budgets is shown in Figure 19.

Figure 19. Distribution of Estimated Contractor Capacities



Contractor-level performance curves were then developed using the same interpolation approach as the month level curves in Chapter 3. Values beyond 100 percent of capacity were extrapolated using the trend from 0 to 100 percent. A sample of four of the highest and lowest capacity contractor curves are shown in Figure 20.

Figure 20. Contractor Capacity Curves

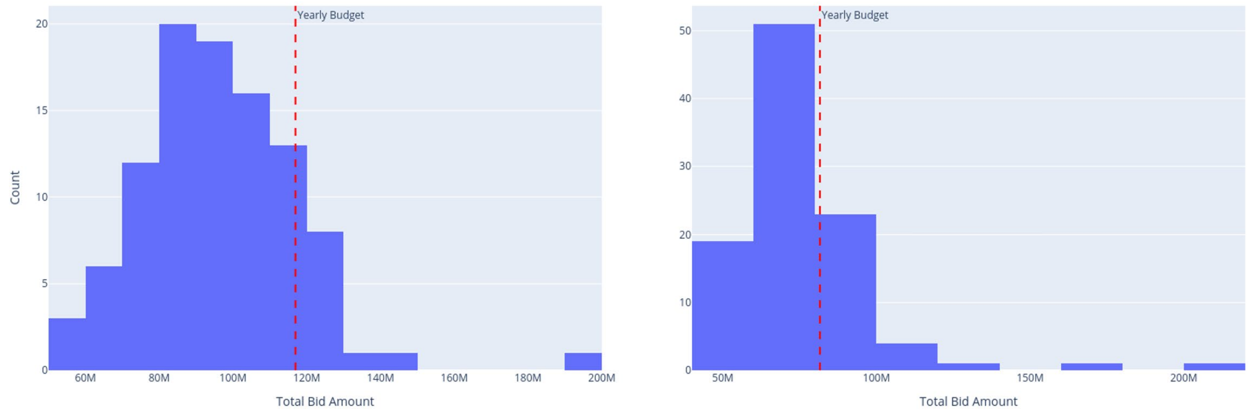


Simulation runs proceeded month by month (June through May). Within each month, projects were ordered to mirror the penalty-curve logic highlighted above (smallest projects placed near the ends of the sequence and larger projects centered), and the following steps were applied iteratively:

- For the next project in sequence, each contractor's current committed work was tallied to determine its capacity utilization. The firm's performance curve was then read at that utilization to produce an implied bid factor for the project.
- A bidding set of five contractors was drawn at random with probabilities proportional to bid favorability, so that more competitive implied bids were more likely to be sampled while preserving randomness.
- The lowest realized bid among the five was recorded as the winning bid, the project was assigned to the winning contractor, and the contractor's committed workload was updated accordingly.

After all projects in the fiscal year were processed, monthly and annual totals were computed. The experiment was repeated 1,000 times to characterize variability. Results were summarized with standard Monte Carlo statistics (e.g., medians and percentile bands) for total spend, monthly spend, and distributional diagnostics, providing a probabilistic view of how capacity dynamics could affect expected outcomes under alternative letting schedules. A histogram of the value won by the top two winningest contractors by dollar value is shown in Figure 21. Their estimated budgets are shown by the red dashed vertical line. The figure indicates that often the contractors are winning a total project value near their estimated capacity and sometimes winning over that amount.

Figure 21. Example of Contractor Project Wins Relative to Budget Across the Simulation



This Monte Carlo simulation can be used to help validate results generated with the performance curves by coming at the problem from the contractor perspective.

4.3.4. Project Readiness Slippage

A Monte Carlo slippage experiment was implemented to quantify schedule risk when a share of projects proved not ready to let in their assigned month. For each run, the historical or optimized schedule was taken as given. Months were processed in fiscal order, and within each month a random 10 percent of projects were reassigned to a later month by a randomly drawn slip length of one or more months. The resulting "slipped" schedule was then re-scored using the standard bidding procedure and historic median monthly targets. Annual and monthly bid totals were recorded. This experiment was repeated 1,000 times to generate distributions of total cost and month-level outcomes.

The analysis indicated that schedule slippage increased expected costs relative to the original schedule, with variability that reflected both the fraction of projects that slipped and the slip lengths. The 10 percent slip rate was treated as an assumption that could be calibrated to observed readiness data (and was not available for this research). The procedure was suitable for integration into a future decision tool to test alternative slip rates and to evaluate the cost effect of proposed schedule adjustments.

4.4. Evaluation Metrics

The evaluation focused on how the optimized schedules performed against defined constraints and cost objectives. Visual diagnostics were first used to show optimization behavior. Graphics highlighted month-by-month plots compared optimized allocations to target shares, highlighted any soft-cap pressure (district or project-type), and letting project counts. Summary tables then reported the key comparators for each fiscal year. This included the actual (real-world) awarded totals, the programmed amounts, the optimization result under the same project set and rules, and the algorithm's computed outcome when the historical letting sequence was “scored” without re-scheduling. Finally, Monte Carlo tables summarized uncertainty with percentile bands (e.g., 10th, 50th, and 90th percentile values) for annual totals and month-level outcomes, providing an expected range under capacity variation and readiness slippage. Together, the plots and tables established both compliance with constraints and the magnitude and robustness of potential savings. Example plots from FY 2022 are shown below using the “All” scenario, i.e. with all constraints both soft and hard, active.

Figure 22 shows the target percentage spent by month of the FY total (red diamonds) and the optimization result (blue bar). This visualization was used to determine how well the optimization algorithm performed in reaching monthly targets. Large deviations from targets indicate optimization solutions that provide large savings by not meeting targets.

Figure 22. Target and Optimized Percent of Dollars by Month

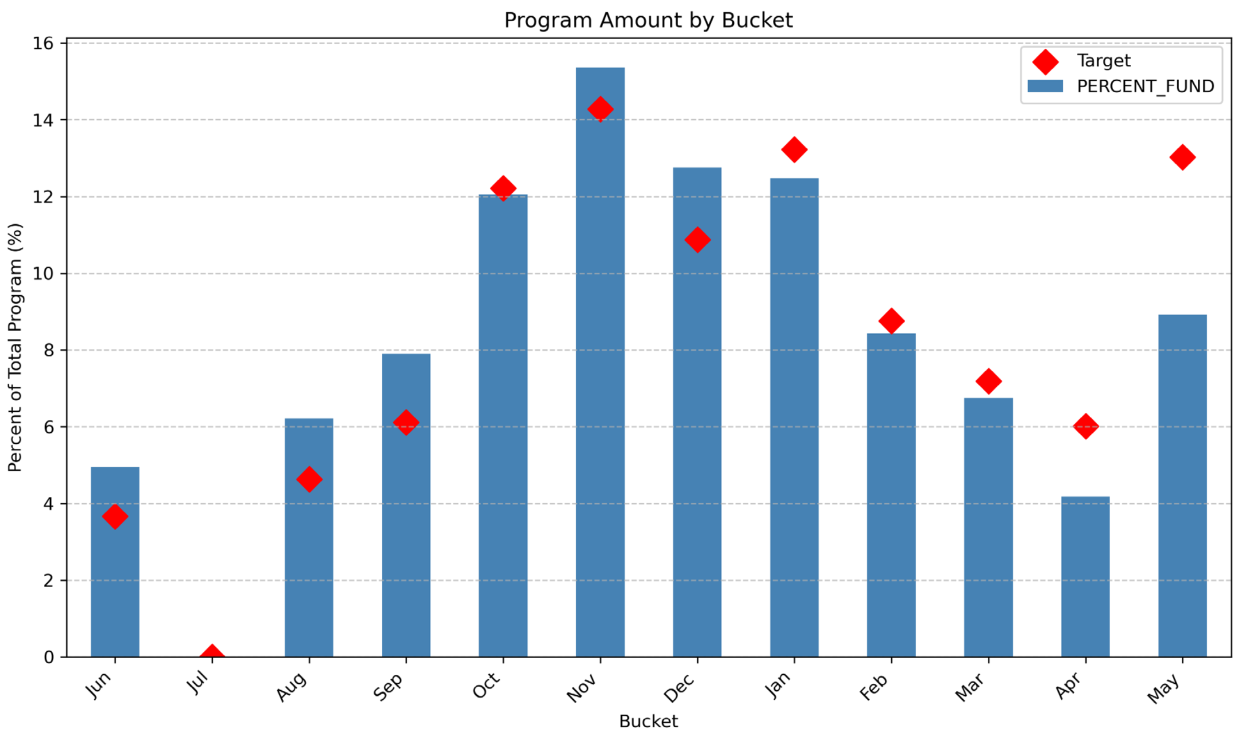


Figure 23 shows the optimized project count by month. This graph was reviewed to ensure that optimized solutions have roughly even distribution across the FY.

Figure 23. Optimized Project Count by Month

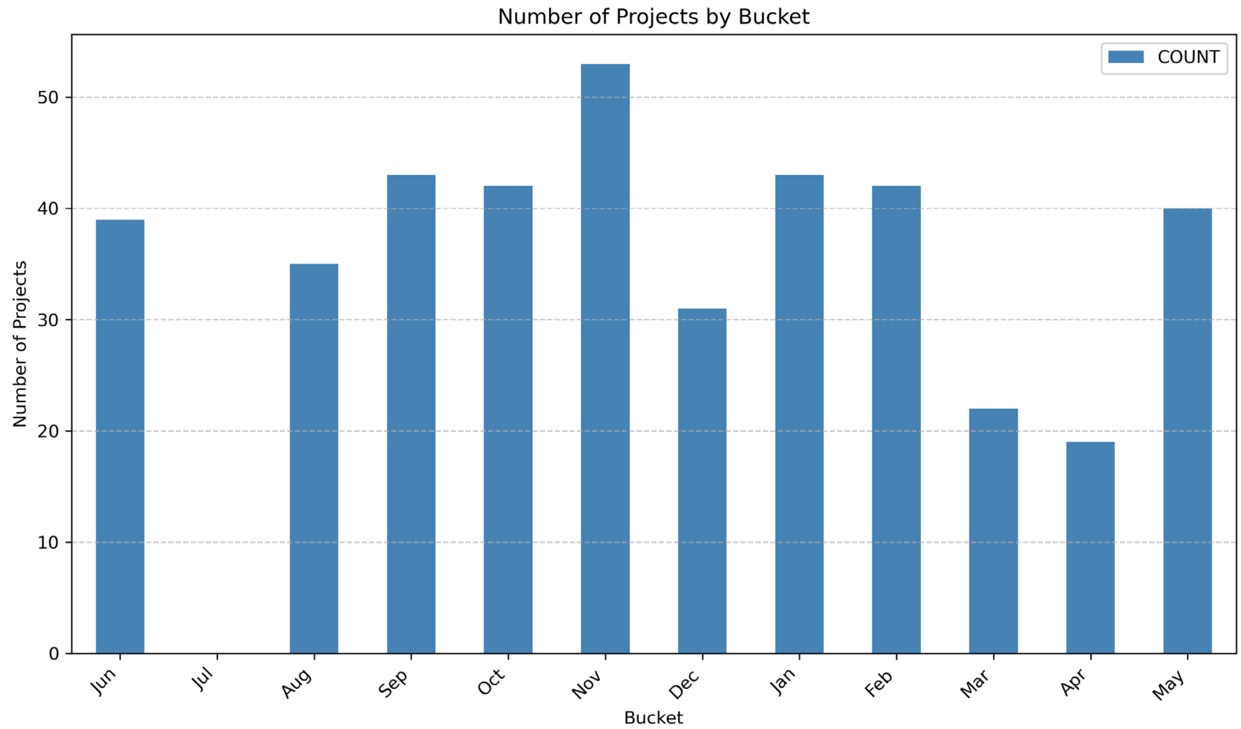


Figure 24. District Spending by Month

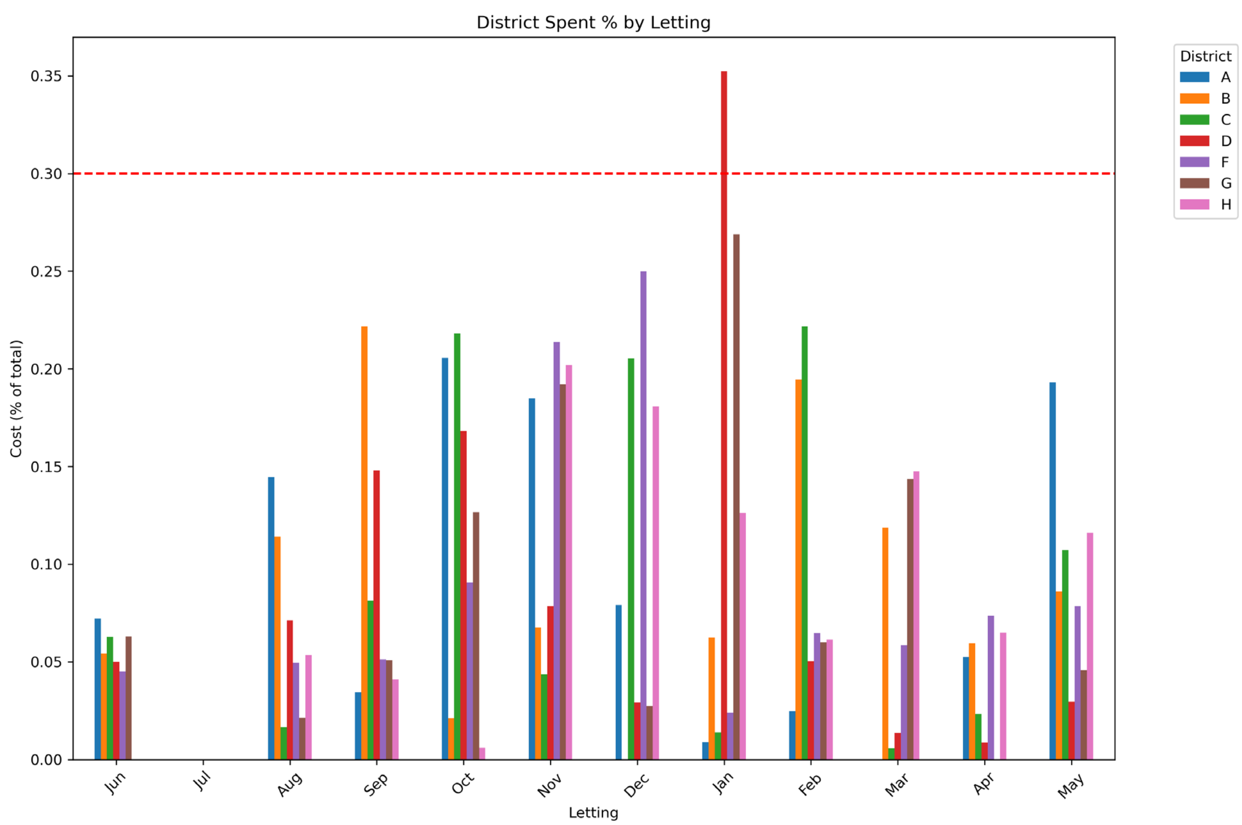


Figure 24 provides insight into the optimized solutions performance related to monthly district spend. The horizontal red dashed line at 30 percent shows the soft constraint limit. In some instances, this constraint was exceeded. This often occurs when large portions of a district's FY spending is isolated around a few large projects or project calls/bundles. In this graph District D goes over the maximum allowed 30 percent in January. Remember that the district constraint is a soft constraint, which means the algorithm allows it to be broken, though a severe penalty is incurred by doing so. The algorithm decided it was worth breaking a single district letting constraint because it resulted in significant overall savings in the total bid.

Figure 25 through Figure 28 shows the target minimum percentage spent by month of the FY total (red diamonds) and the optimization result (blue bar) for paving, bridge, and SSGL project types. This visualization was used to determine how well the optimization algorithm performed in reaching monthly targets. Large deviations below targets indicate optimization solutions that provide large savings by not meeting targets.

Figure 25. Paving Target and Optimized Percent of Dollars by Month

Figure 25

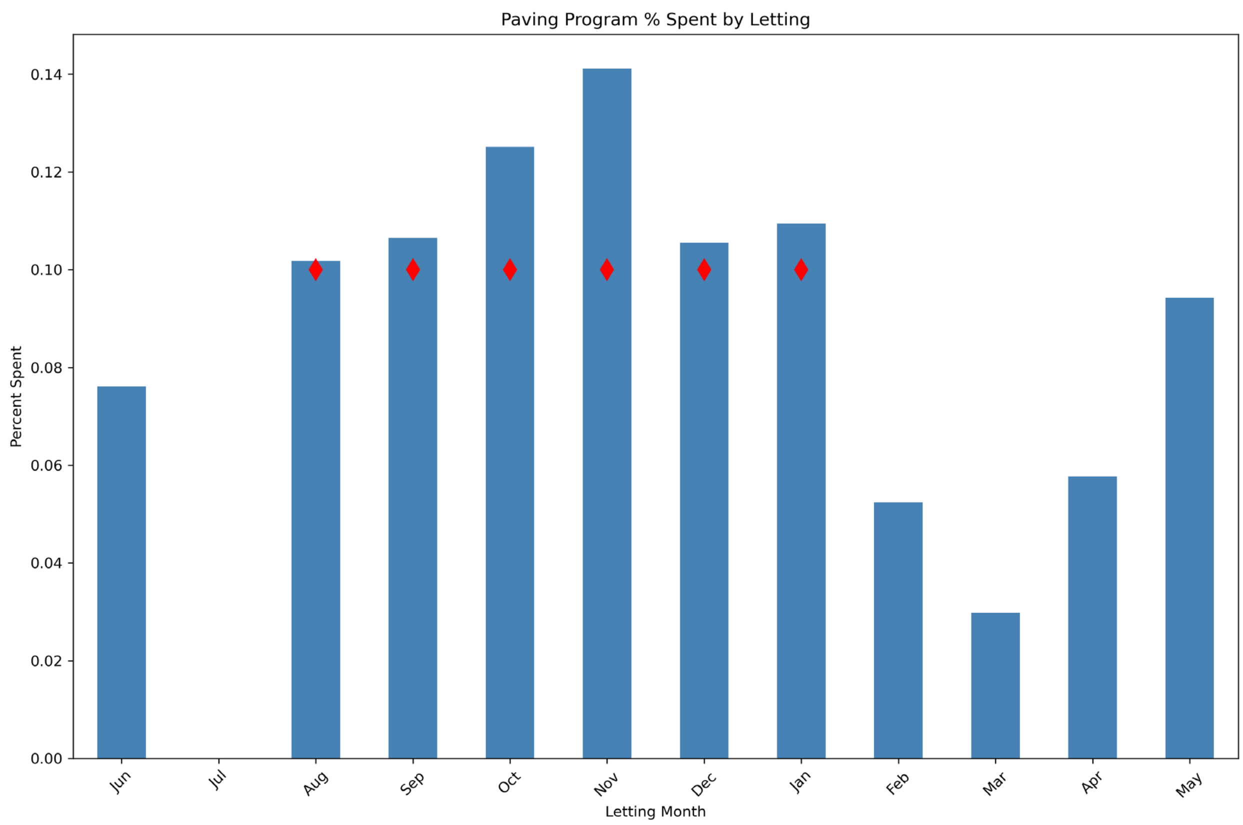


Figure 26. Bridge Target and Optimized Percent of Dollars by Month

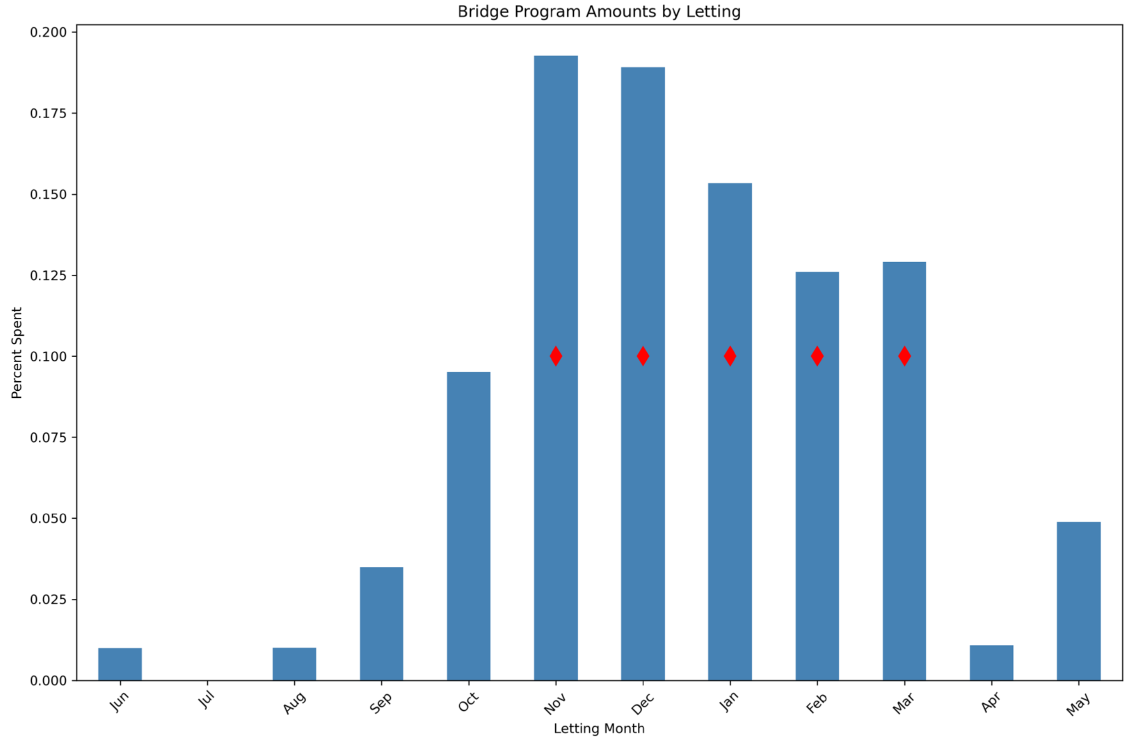


Figure 27. SSGL Target and Optimized Percent of Dollars by Month

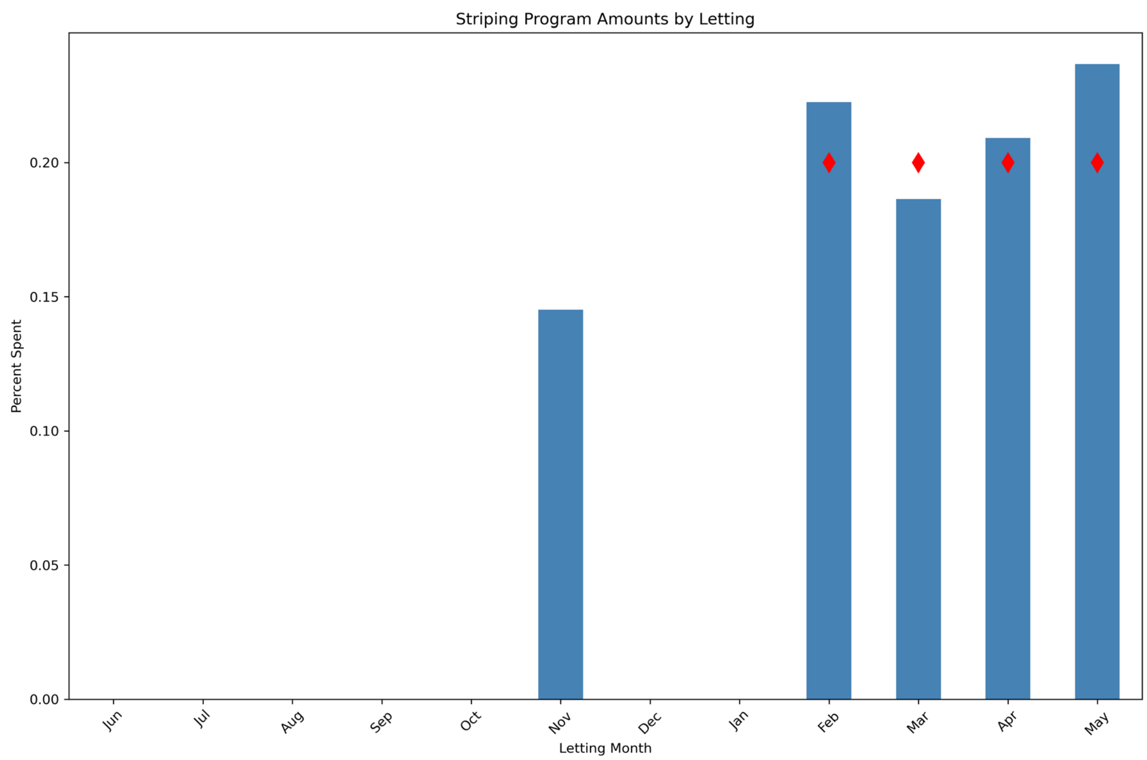
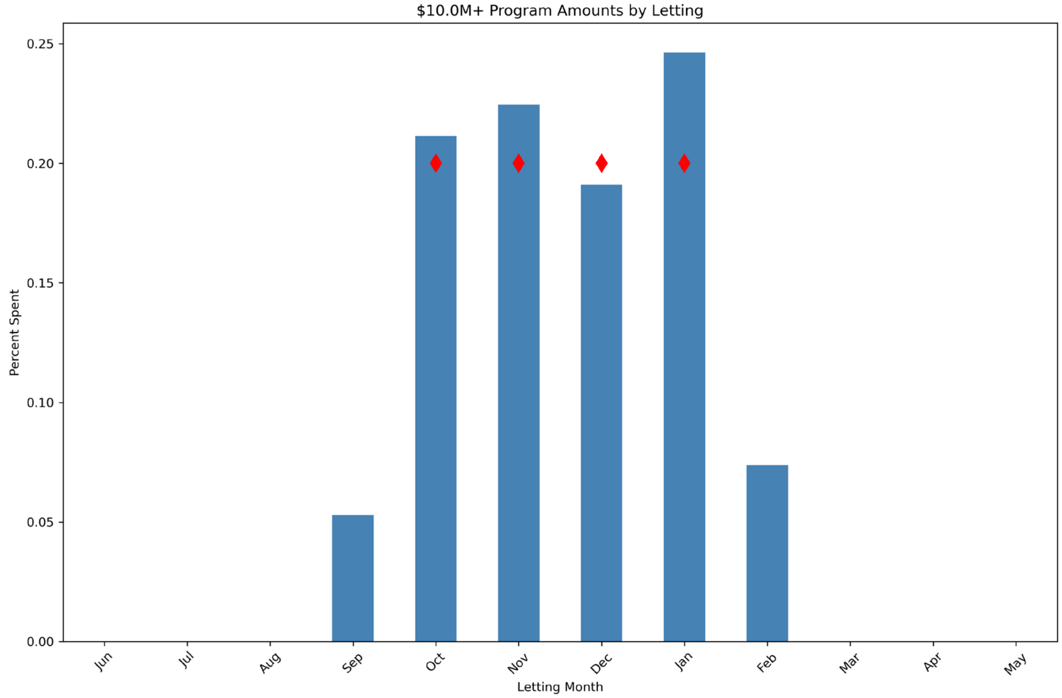
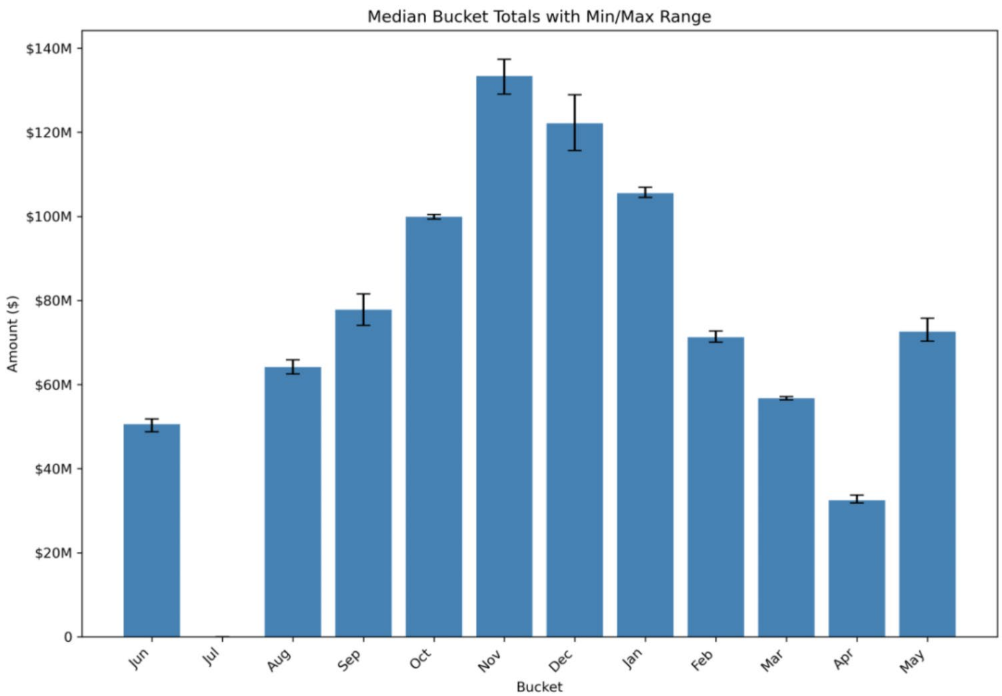


Figure 28. Large Project Target and Optimized Percent of Dollars by Month



Similar to the diagnostic charts above. Bar charts with whiskers were developed for Monte Carlo simulation results showing ranges of expected cost outcome. An example from the monthly redistribution simulation is shown in Figure 29.

Figure 29. Monthly Redistribution Monte Carlo Example Results



Finally, a series of tabular results were developed to compare optimization results with real world values. This was completed for all scenario results outlined in Section 4.2 (Table 17). Monte Carlo results for simulations outlined in Section 4.3 were tabularized, an example table for monthly reordering is shown in Table 18. Table 17 provides the actual low bid amount for the FY, the value the algorithm would compute using the actual letting schedule, the programmed amount, and the optimized value. Table 18 shows the 10th, median, and 90th percentile values for a given Monte Carlo analysis for all scenarios. These values can be used and compared to values in Table 17 to show expected variance.

Table 17. Tabular Optimization Results

Scenario	Actual	Actual Algo	Programmed	Optimized
Actual	-	-	$890M	-
Monthly Distribution (Base)	$1.036B	$921.4M	$890.1M	$849.2M
All - Large Excluded	$1.036B	$921.4M	$890.1M	$872.3M
All	$1.036B	$921.4M	$890.1M	$871.9M
Base + District	$1.036B	$921.4M	$890.1M	$853.4M
Base + Pave	$1.036B	$921.4M	$890.1M	$857.5M
Base + Bridge	$1.036B	$921.4M	$890.1M	$853.8M
Base + Stripe	$1.036B	$921.4M	$890.1M	$852.1M
Base + All - Large - Districts	$1.036B	$921.4M	$890.1M	$855.2M
Base + All - Large + New Bridge Targets	$1.036B	$921.4M	$890.1M	$859.5M
All with New Monthly Distribution	$1.036B	$921.4M	$890.1M	$860.9M

Table 18. Tabular Monte Carlo Results (Monthly Reordering)

Scenario	10th Percentile	Median	90th Percentile
Actual	-	-	-
Monthly Distribution (Base)	$851.7M	$863.1M	$878.5M
All - Large Excluded	$876.7M	$887.1M	$898.9M
All	$876.0M	$886.4M	$897.9M
Base + Dist.	$855.3M	$863.8M	$871.7M
Base + Pave	$861.0M	$869.2M	$879.3M
Base + Bridge	$853.6M	$863.4M	$873.0M
Base + Stripe	$852.5M	$861.6M	$869.4M
Base + All - Large - Districts	$858.5M	$870.8M	$884.0M
Base + All - Large + New Bridge Targets	$864.7M	$874.9M	$887.8M
All with New Monthly Distribution	$862.3M	$872.2M	$881.3M

Together, these diagnostic graphics and tables established that candidate schedules adhered to practical guardrails while pursuing lower expected awards, and that conclusions were stable across uncertainty ranges. The figures clarified where constraints were met or intentionally relaxed, which districts or project types created binding pressure, and how month-by-month counts and dollars shifted under each scenario. The summary tables then anchored those patterns to dollars, showing how optimized outcomes compared with programmed amounts, historical awards, and the algorithm's scoring of the historical sequence. Monte Carlo results bounded plausible variability and indicated where risk to savings concentrated by month. With the evaluation framework in place, the next section reports scenario results for all FYs, interprets program-level savings and trade-offs, and identifies the operational rules that emerged as most effective for annual schedule development.

4.5. Optimization Results

This chapter reports how the optimized letting schedules performed relative to actual results when applied to historical fiscal years with both a high and low amount of constraints, as well as the district + project type optimization approach. These results are followed up with takeaways from the Monte Carlo simulations completed on optimized letting results. A discussion of results when the optimization algorithm was applied to future year FY 2027 is also included.

4.5.1. Optimization Results

Two complementary tables were used to frame the results. In the first, the optimization was run with only the historical monthly distribution targets (the "base" scenario). In the second, the optimization was run with the full set of balancing elements that reflected practice, including monthly targets by project type, large-project handling, and district soft caps (the "all" scenario).

For each fiscal year, seven quantities were shown side by side: program value, the historical total of awarded bids, the algorithm's computed total when the historical letting sequence was scored, the algorithm's computed total for the optimized sequence, and the implied savings between those two algorithmic totals. A scale factor was then applied that equaled the ratio of the historical awards to the algorithm's score of the historical schedule. Multiplying savings by this factor produced a scaled savings measure that adjusted for any systematic over- or under-prediction in the penalty curves.

The intent of this structure was to separate scheduling effects from model fit and to provide an apples-to-apples comparison across fiscal years. The "base" runs showed what could have been achieved by smoothing monthly allocations alone. The "all" runs showed the achievable savings while respecting additional program guardrails that mattered operationally.

Table 19. Results from Base Optimization

FY	Programmed Amount	Actual Let	Actual Let w/ Algorithm	Optimized Let	Optimized Savings	Scale Factor	Scaled Savings	% Savings
FY17	$739.6M	$679.4M	$766.3M	$712.2M	$54.12M	95.40%	$51.63M	6.98%
FY18	$787.1M	$694.4M	$849.3M	$757.1M	$92.23M	91.73%	$84.60M	10.75%
FY19	$710.9M	$682.3M	$716.4M	$679.0M	$37.42M	100.49%	$37.60M	5.29%
FY20	$855.6M	$842.4M	$926.1M	$823.7M	$102.4M	102.27%	$104.7M	12.24%
FY21	$663.7M	$611.9M	$657.2M	$634.6M	$22.60M	96.42%	$21.79M	3.28%
FY22	$890.1M	$1.036B	$932.4M	$849.8M	$82.55M	121.96%	$100.7M	11.31%
FY23	$1.110B	$1.340B	$1.132B	$1.089B	$42.64M	123.04%	$52.47M	4.73%
FY24	$933.4M	$939.5M	$982.9M	$902.2M	$80.71M	104.13%	$84.04M	9.00%

The mean and median scaled savings from the “base” optimization (monthly distributions only) were 7.95 percent and 7.99 percent, respectively, or $79.5M or $79.9M on $1B programmed budget.

Table 20. Results from All Optimization

FY	Programmed Amount	Actual Let	Actual Let w/ Algorithm	Optimized Let	Optimized Savings	Scale Factor	Scaled Savings	% Savings
FY17	$739.6M	$679.4M	$766.3M	$720.7M	$45.58M	94.27%	$42.97M	5.81%
FY18	$787.1M	$694.4M	$849.3M	$773.8M	$75.47M	89.74%	$67.73M	8.60%
FY19	$710.9M	$682.3M	$716.4M	$699.2M	$17.19M	97.58%	$16.77M	2.36%
FY20	$855.6M	$842.4M	$926.1M	$847.1M	$78.95M	99.45%	$78.52M	9.18%
FY21	$663.7M	$611.9M	$657.2M	$652.4M	$4.783M	93.79%	$4.486M	0.68%
FY22	$890.1M	$1.036B	$932.4M	$872.0M	$60.36M	118.86%	$71.74M	8.06%
FY23	$1.110B	$1.340B	$1.132B	$1.122B	$10.24M	119.49%	$12.24M	1.10%
FY24	$933.4M	$939.5M	$982.9M	$921.0M	$61.93M	102.01%	$63.17M	6.77%

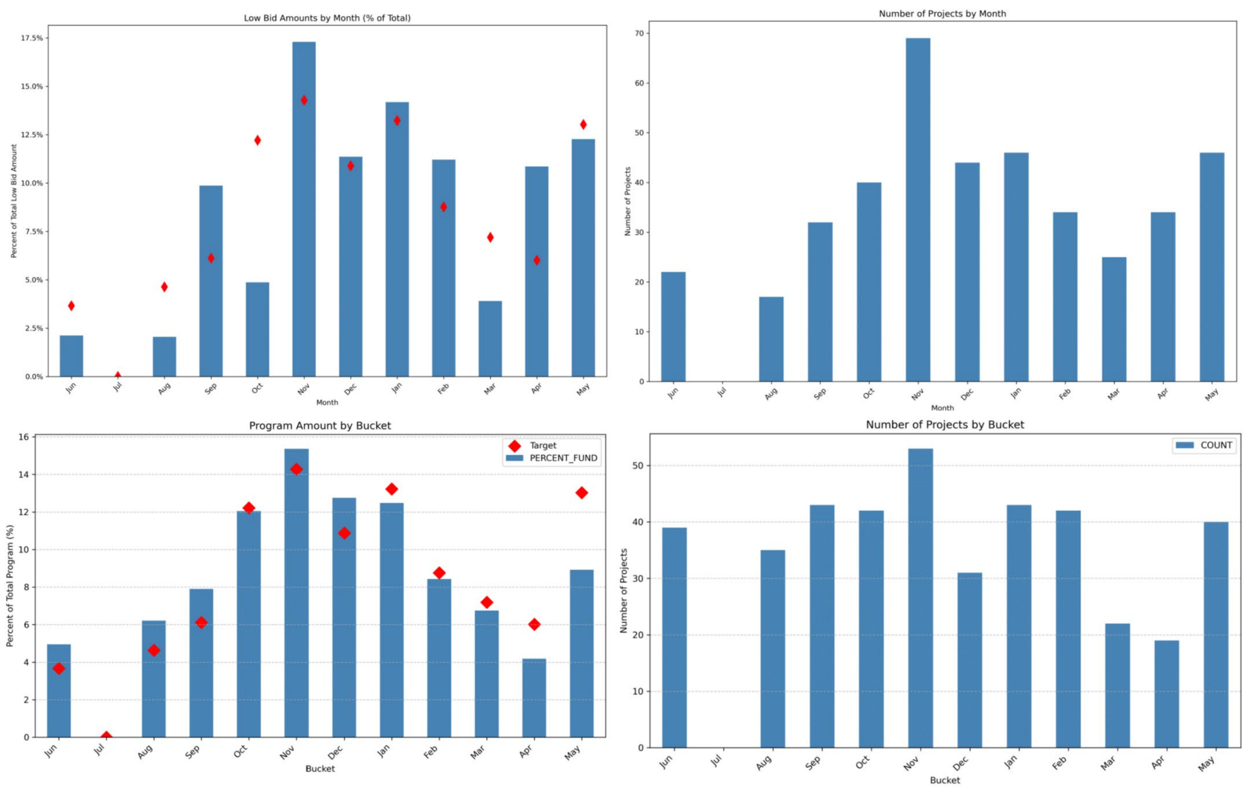
The mean and median scaled savings from the “all” optimization (monthly distributions only) were 5.32 percent and 6.29 percent, respectively, or $53.2M or $62.9M on $1B programmed budget.

Together these tables indicate several interesting findings. Across all fiscal years and constraint sets, the optimized schedules were found to reduce projected award totals. Under the lighter configuration that honored only the historical monthly distribution, scaled savings ranged from 3.28 percent (or $21.8M) for FY 2021 to 12.2 percent (or $104.7M) for FY 2020, with a median of 7.99 percent (or $68.3M).

When the full set of guardrails was respected in the “all” scenario, savings remained material, spanning 0.7 percent (or $4.5M) for FY 2021 to 9.2 percent (or $78.5M) for FY 2020, with a median of 6.29 percent (or $53.1M). The difference between the two medians, 1.7 percent (or $15.2M), represented a 22.3 percent reduction in overall savings attributable to meeting the additional operational constraints. Even so, the algorithm was observed to meet those constraints closely while preserving most of the attainable savings, indicating robust performance under practical policy and scheduling requirements.

When digging into where savings are being achieved, the general trend is that projects are being moved out of April and May, back into fall and winter months. An example from FY 2022 is shown in Figure 30 below. In Figure 30 the top row of images is what actually happened and the bottom row is the optimization result. The left side is percent of FY dollars by month and the right is the project count. The figures show that project distribution across months is more even and that projects are shifted from November, April, and May to other shoulder months where better bids are expected.

Figure 30. Where Savings are Realized



Generally, for all other scenarios the monetary results land near the base scenario as the additional single constraint is often not enough for the algorithm to start having to make tradeoffs. It’s able to hit the constraint while successfully balancing against month targets. Savings only start to be reduced after stacking many of the possibles constraints.

An interesting finding from the scenario with the new monthly distribution that pushed targeted spending away from May and November is shown in Table 21. Historic Monthly Targets vs. Ideal Monthly Targets. The table shows that the average and median annual savings are $5.6M (0.69 percent) and $7.1M (0.79 percent), respectively, simply by changing targets to earlier savings compatible months.

Table 21. Historic Monthly Targets vs. Ideal Monthly Targets

FY	Historic Monthly	New Monthly	Savings	Savings %
FY17	$720.7M	$725.0M	$-4.308M	-0.60%
FY18	$773.3M	$771.2M	$2.115M	0.27%
FY19	$699.0M	$687.5M	$11.47M	1.65%
FY20	$846.8M	$838.7M	$8.152M	0.97%
FY21	$651.7M	$644.3M	$7.397M	1.14%
FY22	$871.9M	$860.9M	$11.02M	1.27%
FY23	$1.121B	$1.115B	$6.834M	0.61%
FY24	$920.4M	$918.5M	$1.920M	0.21%

4.5.2. District + Project Type Results

Review of results from the optimization approach that utilized district + month curves and project type + month curves showed less savings than the base approach, highlighted in Table 22. The mean and median savings using the base approach were $7.8M and $9.6M, respectively.

Table 22. Base vs. District + Type Result Comparison

FY	Base Scenario	District +Type Method	Savings
FY17	$712.2M	$717.3M	$5.162M
FY18	$757.1M	$768.8M	$11.76M
FY19	$679.0M	$690.3M	$11.28M
FY20	$823.7M	$831.5M	$7.841M
FY21	$634.6M	$639.9M	$5.264M
FY22	$849.8M	$862.5M	$12.68M
FY23	$1.089B	$1.082B	$-6.953M
FY24	$902.2M	$918.0M	$15.72M

This suggests that the curves used for district and those used for project type are not compatible or are out of alignment. For example, in reviewing heatmaps from the appendix, the Northwest District has the best performance in January, but bridge projects perform best in October through December. Further, for this optimization technique to be used in the future, districts would be required to come up with their own monthly targets as a percentage of their FY program, and targets for when they would want to let given project types. The base historical assumptions for these, which could be used as a starting point, were recapped in Table 15 and Table 16.

While not explicitly used in the optimization analysis, performance curves for each district/project type/month were created and provided in Appendix A. However, this was only completed for bridge and paving projects as the sample size was insufficient for other project types. Even with bridge and paving projects, some district/project type/month pairs did not have sufficient data to produce a curve.

4.5.3. Monte Carlo Results

4.5.3.1. Expected Ranges from Monte Carlo Testing

The Monte Carlo experiments of all three types give us natural ranges of expected outcomes of a particular letting's total bids. These ranges can be used to estimate variation in expected savings. Table 23 illustrates the results of performing those analyses on all three types of Monte Carlo simulations.

Table 23. Monte Carlo Expected Ranges

FY	Curve Reordering		Curve Random		Contractor Bidding	
	Low	High	Low	High	Low	High
FY17	99.34%	100.84%	97.67%	102.87%	96.84%	109.71%
FY18	99.23%	100.93%	97.50%	103.68%	96.54%	109.79%
FY19	99.16%	100.82%	97.77%	103.14%	97.22%	106.81%
FY20	99.25%	100.59%	97.70%	103.28%	96.38%	108.97%
FY21	99.00%	101.30%	97.92%	102.27%	97.34%	106.28%
FY22	98.83%	101.30%	97.39%	103.01%	96.22%	108.43%
FY23	99.26%	100.73%	98.00%	102.31%	95.93%	106.49%
FY24	99.01%	100.98%	97.97%	102.21%	96.81%	107.11%

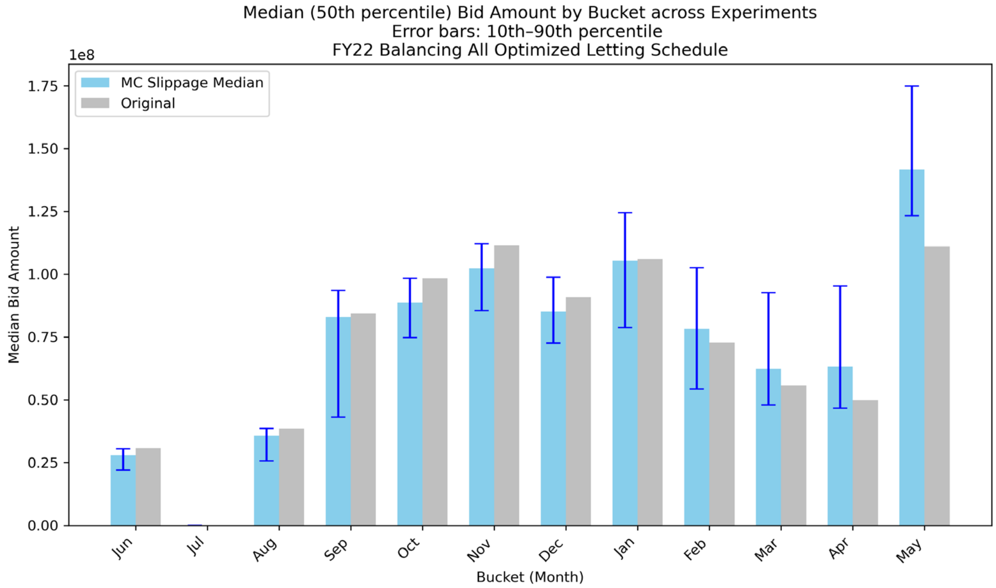
The narrowest uncertainty band was produced by the curve-reordering analysis, which indicated outcomes about 0.8 percent lower to 0.9 percent higher than the optimized baseline. The intermediate band from the random-curve placement analysis yielded a range of roughly 2.25 percent lower to 3 percent higher. The widest expectations arose from the contractor bidding analysis, with totals approximately 4.5 percent lower to 8 percent higher under the modeled assumptions.

Results from the contractor-bidding analysis were found to align closely with the optimization outcomes, despite the fundamentally different methods used to generate project bid costs. This convergence suggested that contractor capacity and backlog dynamics were already embedded in the empirically derived monthly performance curves. Given the added assumptions required for contractor-specific curves and the comparable results, it is recommended that the simpler monthly curves be used for decision support, and the contractor bidding analysis be used to estimate expected variance.

4.5.3.2. Slippage

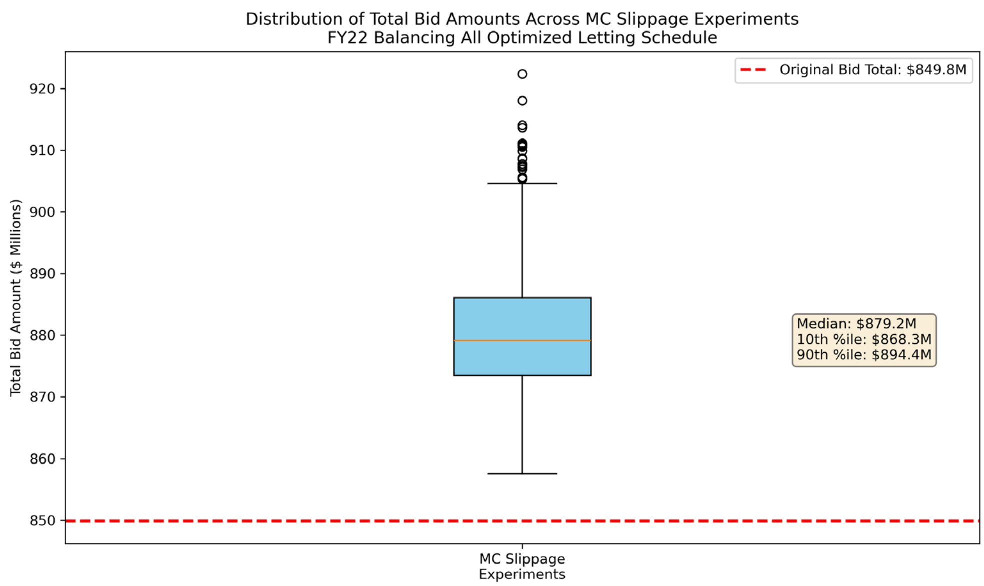
The Monte Carlo slippage results showed little to no uplift in July through August and essentially none in October and November. December marked the inflection where slippage began to raise monthly bid totals, and from January through May both the median and spread (10th–90th percentile) increased steadily, peaking in May, indicating that schedule slippage in late winter and spring compounded costs the most. Slippage results from FY 2022 are shown in Figure 31.

Figure 31. Slippage Results for FY 2022



Further, Figure 32 shows the distribution of slippage results. In all Monte Carlo slippage experiments, total costs were increased relative to the optimized letting baseline, as expected when schedule deviations were introduced. The distribution of outcomes was characterized by a 10th to 90th percentile range of $868.3M to $894.4M, which was interpreted as a likely interval for annual totals under plausible slippage. Consequently, a practical worst-case threshold was identified: there was an estimated 10 percent probability that costs would exceed $894.4M, implying 90 percent confidence that the optimized total of $849.8M would not slip beyond that level under the modeled assumptions.

Figure 32. Distribution of Slippage Results for FY 2022



Finally, when extrapolating this across all FYs, if approximately 10 percent of projects slip each month (about four projects per month), it is estimated that this is costing the department a median of 2.78 percent (see Table 24) in additional costs per FY, or $27.8M on a $1B letting. Remember that with 10 percent of projects slipping, out of $1B program, that means on average $100M of projects are slipping, which means that the additional $27.8M related to those $100M worth of projects.

Table 24. Monte Carlo Slippage Results by FY

FY	Base Optimized Value	Slippage Median Value	Difference	Percent Difference
FY17	$712.2M	$732.1M	$19.97M	2.80%
FY18	$757.1M	$777.8M	$20.79M	2.75%
FY19	$679.0M	$698.7M	$19.67M	2.90%
FY20	$823.7M	$845.0M	$21.32M	2.59%
FY21	$634.6M	$654.7M	$20.14M	3.17%
FY22	$849.8M	$879.5M	$29.66M	3.49%
FY23	$1.089B	$1.111B	$21.36M	1.96%
FY24	$902.2M	$918.6M	$16.34M	1.81%

4.5.4. Future Year Results

The optimization was run using the future FY 2027 program to test how optimized value compared to the estimated program amount after assigning a letting schedule. The base, all, and new distribution results are shown in Table 25.

Table 25. FY 2027 Optimization Results

Scenario	Programmed	Real Algo Prediction	Optimized	Predicted Savings
Base	$1.271B	$1.283B	$1.214B	$69.63M
All	$1.271B	$1.283B	$1.219B	$64.20M
All with New Monthly Distribution	$1.271B	$1.283B	$1.219B	$64.23M

The table shows the estimated program value, and the optimized expected low bid value. Additionally, an algorithm prediction of historical performance was estimated by comparing historical fiscal years programmed values to algorithm estimated program value (this can be done with historical years because actual letting schedules are available). This amount was approximately 1 percent. The predicted savings was computed by taking the difference of the algorithm estimation and the optimized value, similar to how historical results were calculated earlier in the chapter.

The results show predicted savings of between $64M and $70M for FY 2027's optimization results, depending on the optimization scenario. Additionally, the base scenario shows the greatest savings as there is more flexibility in project letting placement, resulting in about $5M in additional savings. Further, the new distribution, where projects are shifted away from

November and May, does not show any additional savings compared how MoDOT has been letting historically.

4.6. Optimization Analysis Conclusions

The optimization analysis demonstrated that MoDOT's letting calendar can be systematically adjusted to reduce expected bid amounts (between 5 and 8 percent per FY) while staying largely within current operational guardrails. By combining empirically derived monthly performance curves with a flexible genetic algorithm, the optimization exercise translated historical bidding behavior into concrete schedule changes, rather than relying on abstract assumptions about market response. The approach handled realistic constraints, including eligibility windows, bundling, monthly targets, district caps, and project-type timing preferences while remaining computationally tractable and auditable.

Across historical fiscal years, the "base" optimization scenarios showed that simply redistributing programmed dollars across the year, guided by the monthly performance curves and historic targets, consistently lowered expected award totals. When additional guardrails were layered in, the "all" scenarios, still delivered material savings, albeit at a reduced level. In other words, MoDOT can preserve a large share of theoretical savings while honoring practical requirements about when and how work is let. The results also showed where savings tend to come from in practice. Mainly, reducing concentration in April and May and shifting work back into fall and winter months where bids have historically been more favorable, while maintaining a reasonable, if not more uniform, distribution of monthly project counts.

Scenario tests around alternative monthly distributions and more nuanced district + project-type penalty curves provided important context for implementation. Modestly shifting targets away from May and November produced small but persistent additional savings, suggesting that refining MoDOT's target monthly distributions is a low-risk, incremental lever. In contrast, the district + project-type penalty approach to optimization produced less savings and highlighted misalignments between district-level and project-type curves. This suggests that while more granular curves can be analytically interesting, the monthly performance curves are the more practical primary tool for routine decision support, with district and project-type patterns better used as diagnostic context rather than as the main optimization engine.

The Monte Carlo experiments reinforced the robustness of these conclusions and quantified the range of outcomes under uncertainty. Within months reordering and random monthly curve placement simulations showed that optimized savings are not an artifact of a single project sequence. Expected totals remained favorable within relatively narrow bands. The contractor-bidding simulation, built from contractor-specific capacity curves, produced results consistent with the simpler monthly-curve framework, indicating that capacity and backlog dynamics are already embedded in the empirical performance curves. The slippage experiments underscored the importance of project readiness. Even a 10 percent slip rate, on the order of approximately four projects per month, can add roughly 2 – 3 percent to annual costs, with the largest impacts when slips push work into late winter and spring months.

Finally, applying the optimization framework to the future FY 2027 program indicated that similar patterns and savings are achievable going forward, with predicted reductions on the $60 – $70M depending on the constraint set. This prospective result suggests that algorithmic optimization is not just a retrospective diagnostic tool but a practical forward-looking planning aid.

Taken together, this establishes that MoDOT's letting schedule is a powerful, controllable lever for managing bid outcomes, that empirical performance curves provide a defensible basis for adjusting that schedule, and that uncertainty and slippage can be quantified and planned for rather than treated as unknowable noise.

The next chapter turns from analysis to action, translating these findings into specific policy recommendations, how MoDOT should target months for advertising and letting different types of projects, and how project timing and contractor workload can be managed to capture savings while maintaining deliverability and program balance.

5. Policy Recommendations

This chapter translates the empirical findings and optimization demonstrations into policy recommendations that could be used in routine letting schedule development. Evidence from historical outcomes, peer practice, and scenario testing was synthesized to identify when advertising was most competitive, how monthly volumes were best smoothed, and how workload pressure and readiness affected price. Practical guardrails were proposed for timing, project mix, district balance, lead time, and transparency, with limits and assumptions noted where data were incomplete but may be desirable.

5.1. When to Advertise Projects for Construction

The following section highlights policy actions that can be pursued to realize demonstrated savings from pilot optimization analyses for when projects should be let.

Convert research findings into a lightweight tool. The tool can take advantage of performance curves and historical monthly targets to produce a draft letting schedule that optimizes savings. The performance curves intrinsically incorporate real world dynamics of seasonal lettings and contractor capacity. Schedules result in significant department savings while simultaneously balancing project count distribution, potentially increasing project delivery by 5 to 8 percent. A tool could be used to refine the letting schedule should projects miss their scheduled dates. The tool could be paired with a monthly or quarterly KPI dashboard set to track performance (e.g. average bids, percent difference from program and optimized estimated totals, backlog estimation, etc.), obtain feedback, and trigger re-tuning cycles. A sample tool mockup is included in Appendix B.

In the absence of a tool, leverage heatmaps in Appendix A. It was demonstrated that different combinations of district, project type, and month do not always follow a strict logical pattern. Some districts have more success with early lettings while others have success with winter lettings. This is true for project type, and certain project types within districts. It was also identified that months where a given project type are let are not aligned with the months when they have best performance. For example, bridges are typically let in November through May but achieve the best savings in August through December. Heatmap use should outperform existing rules of thumb.

Project lettings should target fall and winter months. When given the flexibility to move projects based on historical performance, projects were most often moved out of April and May to fall and winter months. If an optimization tool is developed and implemented, the draft letting schedule could be used to develop individual project schedules in a manner that critical permitting dates are met (e.g. FONSI) such that the letting schedule does not need to be adjusted, and potential savings are lost. This recommendation also does not mean that no projects should be let in April and May. Performance curves indicate that good bid prices are still achieved at lower monthly capacity levels.

Stick to the schedule. A formal schedule-adherence policy is recommended after it was demonstrated that a 10 percent slip in projects increased costs by roughly 2 to 3 percent. Schedules should be set on realistic drivers of complexity (e.g., right-of-way, utilities, permits), with an agreed baseline that is agreed to, and governed by an institutional performance-management structure. Risk slack should be built into critical paths, and routine schedule reviews should be held to surface bottlenecks early and deploy corrective actions (e.g., targeted up-staffing) to protect letting dates. Performance tracking could be institutionalized using MoDOT's existing tools to track items like percent of projects missing target lettings and progress on key milestones, so deviations trigger predefined escalation steps. The quantified cost of slippage from this research, in combination with a future optimization tool, can be used as decision support: when a project slip to a high-cost month is forecast, managers could justify short-term resources to maintain the original letting or, if unavoidable, re-sequence work to the next best window.

Advertise as far in advance as possible. Interviews with industry representatives indicated that the more time and detail available prior to a letting, the better and more accurate estimates they can pull together. This was reinforced by many peer states advertising farther in advance than MoDOT's standard six months. Some states are advertising projects up to a year or two in advance.

Take advantage of AASHTOWare modules. Several of the peer states indicated that they are leveraging the Project Data Analytics module to quickly surface actionable data findings and apply them to their letting practice.

Don't pivot too quickly. While optimization findings have indicated that moving projects out of April and May can result in substantial savings, there was also input from the contractor community, and evidence from KDOT's relatively recent experience, that sudden changes in practice can have negative consequences. The May letting has historically been one of MoDOT's largest volume months, and the contractor community has come to expect this. There was evidence that a target schedule targeting slightly less volume in May does generate modest savings. These targets could be tweaked over time to gradually shift letting volume.

5.2. Estimating/Optimizing Contractor Workload

Develop a contractor backlog dashboard. The exploratory analysis demonstrated that contractor backlog can be approximated from award values and proposed start and end dates using a simple linear burn profile. A production dashboard should be developed to expose this measure at contractor, district, and project-type levels with filters and rollups. Capacity thresholds can be set from historical wins, for example the 67th percentile of each firm's historical annual award value. The dashboard should refresh monthly from award and payment systems and, where feasible, include near real-time post-award updates. District staff can use it to shape upcoming lettings and to pre-market work to likely bidders. The optimization application can read the same feed so scenarios flag months when the preferred bidder set is already near capacity and Monte Carlo ranges widen, prompting schedule deferral or re-sequencing when warranted.

Expand contractor meetings. The Southwest District annual meeting has received rave reviews from industry representatives. They provide an opportunity to engage with MoDOT staff and review the upcoming program, allowing them to not only gain knowledge, but also provide input to MoDOT.

5.3. Other Considerations, Additional Data, and Additional Research

The following items should also be considered by MoDOT when looking to implement the above recommendations:

Simplicity is preferred. If an optimization tool is developed, it is recommended that the tool be developed with the simpler monthly curve method, and layer on additional constraints. This is opposed to using multiple curve approximations (district + type), or the contractor backlog probabilistic bidding method. The monthly curves intrinsically account for the additional detail the other methods try to capture, rely on less assumptions, and could be implemented by any state DOT.

Use engineering estimates. Engineering estimates were not available for this research effort. Should an optimization tool be developed, it is recommended that performance curves be developed using percent difference from engineering estimate versus the programmed amount.

Use actual contractor payment data. The contractor backlog data in this project uses project award values and linear burn rates. It is recommended that should a dashboard be developed, actual contractor payment data be used in lieu of burn rate assumptions.

Account for contractor performance. Contractor performance should be accounted for in analyzing low bid/best value awards compared to contractor backlog. Currently, a full picture is not used in the optimization. A project that is awarded 5 percent below programmed amount, but was actually constructed at 5 percent over programmed amount, due to change orders, poor quality, or schedule overruns, is not a factor. The case could exist that a higher bid from a full contractor might result in a better outcome for the department than a lower bid from an idle contractor that did not perform well.

Account for project complexity. Degree of project complexity was also not considered in the analysis but was discussed with MoDOT. Recommend identifying and tracking a project complexity variable(s) and analyzing the relationship with percent difference between program amount and award amount.

Obtain additional geographic details. Geography was only accounted for at the district level as latitude and longitude geocoding for project and contractor plant locations were not available.

Discussions with the contractor community indicated that this was a strong factor in bid cost and decision to bid. It is recommended that MoDOT geocode let projects, and track contractor plant locations (example from Nebraska DOT: https://gis.ne.gov/portal/apps/experiencebuilder/experience/?id=91716e725fc84d31aebf08115dfeb4d2&page=Page-1&views=Legend#data_s=id%3AdataSource_1-182a30f6b03-layer-6%3A4710). Geography data could be used to develop contractor competitiveness scores, which could be used in combination with the backlog dashboard to identify likely bidders and help adjust the optimized letting schedule.

Coordinate letting time with neighboring states. In situations where large projects are needed to let, and/or FY programs are larger than historical years, the department should coordinate with neighboring states to try and offset larger projects between state programs.

5.4. Summary

This chapter translated analytical evidence and prototype optimization results into pragmatic policy guidance for routine letting schedule development. A lightweight tool based on monthly performance curves was recommended, with heatmaps offered as an interim method when tooling was not available. Policies emphasized targeting fall and winter lettings, adhering to published schedules, extending advertising lead times, and using available AASHTOWare analytics. A contractor backlog dashboard was outlined to support workload awareness and industry engagement, including expanded district meetings. Additional data and research needs were cataloged, including use of engineer's estimates, actual payment data, contractor performance, project complexity, and finer geographic detail, so that implementation could be refined over time.

6. Conclusions

This study demonstrated that letting schedules could be arranged to improve competition and lower award costs while remaining consistent with MoDOT practice and constraints. Historical bidding patterns and peer insights were translated into performance curves, monthly targets, and practical guardrails that were implemented in an optimization prototype. Across fiscal years and scenarios, savings were consistently indicated, with larger gains when schedules were smoothed and late spring concentrations were reduced. Monte Carlo checks showed that the findings were robust to plausible uncertainty and that schedule slippage imposed measurable cost penalties.

Limits and assumptions were documented, including reliance on programmed amounts, simplified backlog proxies, and district level geography. These limits were judged manageable and actionable. Taken together, the evidence supported near-term adoption of a lightweight tool and routine KPI tracking to institutionalize improved schedule development.

Immediate next steps should include:

- A pilot season to generate a draft letting plan using monthly curves and targets, paired with a KPI dashboard, and a contractor backlog dashboard.
- Data refresh processes should be formalized (engineer’s estimates, actual payment data, geocoding) to strengthen future calibrations.
- District and industry engagement to be expanded to reinforce schedule adherence and provide early visibility into upcoming work.

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Appendix A: Performance Curves and Heatmaps

The appendix assembled the full set of monthly performance curves and companion heatmaps used to characterize how letting volume related to bid outcomes first described in Chapter 3. Curves were constructed from awarded projects in FY2016–FY2024, excluding July regular lettings, non-comparable procurements, and JOC contracts from the curve fitting (JOCs were treated as program equals award value). For each month, projects were ordered by percent difference (winning bid minus programmed amount, as a percent of program), cumulative programmed dollars were computed, and values were interpolated onto a common 0.00–1.00 grid of cumulative share. Curves were then averaged across fiscal years.

Heatmaps summarized these same relationships in a tabular form for quick scanning. Rows represented cumulative programmed share at a given percentile of monthly programmed amount and columns represented months (June through May, excluding July). Cell values reported the average percentage difference as a function of total target monthly spend. Lower percentiles indicate less spending compared to historical median and higher percentiles are spent near historical monthly medians. A good way to quickly compare month to month performance is to review the 50th percentile row. Regardless of the variables in the curve, these values typically hover around a zero percent difference (award price near programmed amount). District specific and project-type specific panels were included where sample sizes were sufficient.

A.1. Monthly Performance Curves and Heatmaps

Figure 33 shows the monthly performance curves. These same curves are converted to a heatmap in Table 26.

Figure 33. Monthly Performance Curves

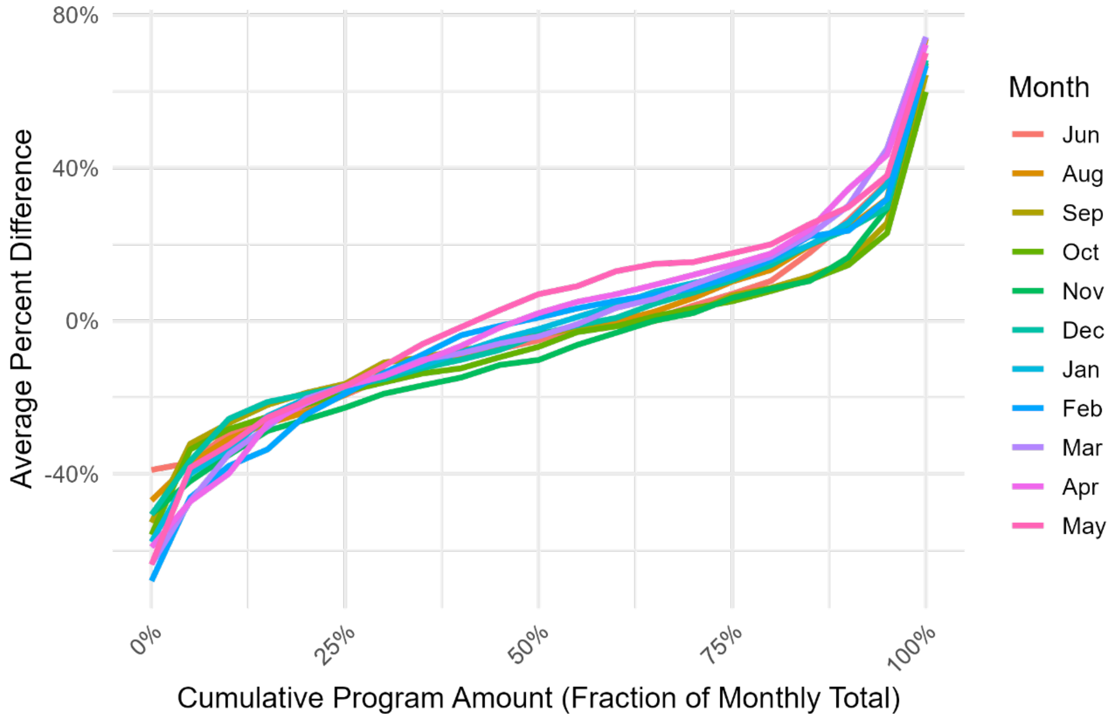

Table 26. Monthly Performance Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-39.0%	-46.9%	-52.7%	-55.9%	-50.5%	-50.6%	-57.8%	-68.0%	-63.7%	-59.1%	-63.7%
0.05	-37.1%	-37.2%	-32.1%	-33.6%	-41.9%	-36.6%	-40.0%	-46.2%	-47.1%	-47.2%	-38.4%
0.1	-29.3%	-30.8%	-26.7%	-28.3%	-35.1%	-25.6%	-33.7%	-37.9%	-34.8%	-39.9%	-32.4%
0.15	-26.3%	-26.8%	-21.9%	-25.1%	-28.7%	-21.2%	-24.9%	-33.6%	-27.7%	-26.9%	-25.2%
0.2	-22.5%	-23.8%	-18.8%	-21.9%	-25.8%	-19.1%	-20.3%	-24.5%	-20.3%	-21.5%	-20.9%
0.25	-19.4%	-19.3%	-16.5%	-18.5%	-22.7%	-17.2%	-17.6%	-19.1%	-17.0%	-17.1%	-17.1%
0.3	-15.0%	-13.4%	-10.9%	-16.1%	-19.0%	-15.2%	-14.3%	-13.6%	-14.2%	-14.5%	-11.8%
0.35	-11.6%	-11.2%	-9.5%	-13.7%	-16.9%	-12.4%	-11.7%	-8.8%	-10.1%	-10.5%	-6.1%
0.4	-9.6%	-8.7%	-7.6%	-12.4%	-14.8%	-10.1%	-8.2%	-3.7%	-8.5%	-6.5%	-1.6%
0.45	-7.4%	-5.6%	-6.4%	-9.5%	-11.5%	-7.6%	-4.8%	-1.3%	-5.9%	-1.7%	2.8%
0.5	-5.1%	-3.3%	-3.6%	-6.8%	-10.2%	-3.5%	-2.1%	0.9%	-4.0%	2.0%	7.0%
0.55	-1.7%	-1.9%	-1.9%	-2.9%	-6.3%	-1.2%	1.0%	3.3%	-0.8%	5.0%	9.1%
0.6	-0.3%	-0.2%	-1.4%	-1.4%	-3.1%	0.8%	4.1%	5.3%	3.4%	7.0%	13.0%
0.65	0.6%	2.5%	0.0%	1.2%	0.1%	4.5%	7.6%	6.8%	5.8%	9.4%	14.9%
0.7	4.0%	6.0%	2.2%	3.3%	2.1%	7.4%	9.9%	8.5%	9.6%	12.1%	15.4%
0.75	7.1%	10.3%	6.7%	5.1%	6.0%	10.6%	11.9%	11.4%	13.2%	14.7%	17.7%
0.8	10.4%	13.3%	8.6%	7.8%	8.4%	14.6%	15.7%	16.2%	16.8%	17.6%	20.0%
0.85	17.8%	19.7%	11.6%	10.7%	10.4%	19.9%	19.8%	22.1%	22.4%	23.9%	25.3%
0.9	26.4%	24.4%	15.6%	14.6%	16.6%	24.0%	25.7%	23.6%	30.1%	34.5%	29.8%
0.95	36.2%	32.0%	25.6%	22.9%	29.4%	29.7%	35.8%	31.9%	45.0%	43.4%	38.0%
1	67.3%	73.8%	64.3%	59.9%	67.5%	68.2%	66.8%	66.6%	74.3%	72.2%	70.1%

The heatmap indicates that September through November are the months most likely to receive the best bids across most levels of expected spend.

A.2. District Performance Curves and Heatmaps

District performance curves are shown in Figure 34 and heatmaps are shown in Table 27 through Table 33. The heatmaps indicate that most districts are unique and should target specific months (e.g. Northwest District has success in January while Northeast has success in August, and Southeast District has had success in atypical months like May and June.)

Figure 34. District Month Performance Curves

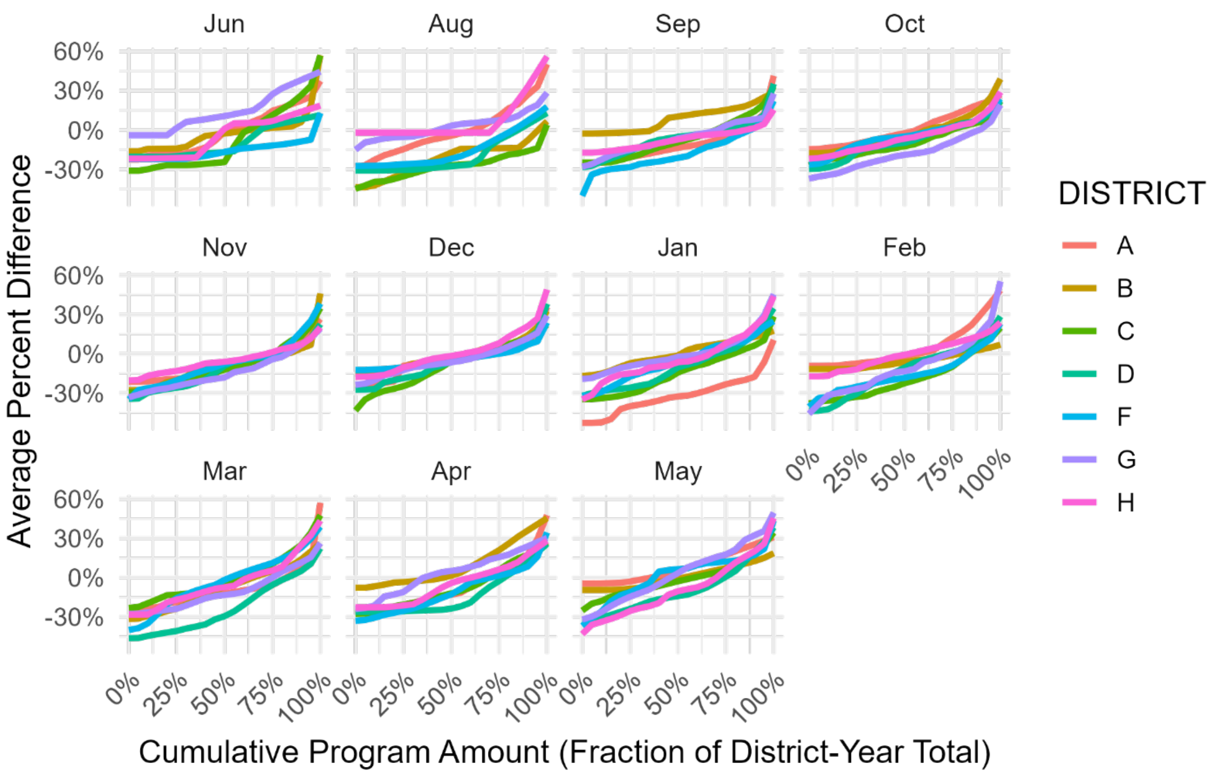

Table 27. Northwest District Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-22.4%	-27.9%	-26.9%	-14.6%	-21.4%	-24.3%	-52.8%	-9.2%	-23.2%	-24.9%	-4.5%
0.05	-22.4%	-26.8%	-26.7%	-14.4%	-21.4%	-24.3%	-52.8%	-9.2%	-23.2%	-24.9%	-4.5%
0.1	-19.4%	-22.7%	-24.4%	-13.6%	-21.0%	-22.9%	-52.4%	-9.2%	-23.2%	-24.9%	-4.5%
0.15	-19.0%	-19.3%	-23.2%	-12.8%	-20.3%	-22.3%	-49.9%	-8.9%	-22.6%	-23.7%	-4.2%
0.2	-18.7%	-17.0%	-22.0%	-12.0%	-19.5%	-21.1%	-42.3%	-8.2%	-19.8%	-22.4%	-4.0%
0.25	-18.5%	-14.7%	-20.7%	-10.4%	-19.0%	-9.2%	-40.0%	-7.4%	-18.7%	-20.9%	-3.0%
0.3	-17.9%	-11.8%	-19.3%	-8.8%	-18.5%	-7.6%	-38.8%	-6.6%	-17.4%	-19.2%	-1.7%
0.35	-15.7%	-9.2%	-18.0%	-7.2%	-16.7%	-7.0%	-37.4%	-5.8%	-16.2%	-17.5%	-0.3%
0.4	-13.3%	-7.3%	-16.5%	-5.6%	-15.6%	-6.1%	-35.7%	-4.7%	-14.9%	-15.8%	1.1%
0.45	-8.2%	-5.9%	-15.0%	-3.9%	-13.9%	-5.1%	-33.7%	-3.4%	-13.6%	-14.1%	2.8%
0.5	-1.4%	-4.4%	-13.6%	-2.4%	-11.2%	-3.9%	-32.6%	-1.7%	-12.3%	-13.2%	5.0%
0.55	1.4%	-2.5%	-12.5%	-0.7%	-6.7%	-2.8%	-31.9%	-0.2%	-11.0%	-11.6%	7.3%
0.6	3.7%	-0.7%	-11.2%	2.7%	-5.7%	-1.1%	-30.2%	0.9%	-9.7%	-7.1%	9.6%
0.65	6.6%	2.1%	-9.6%	6.2%	-5.1%	0.8%	-28.2%	2.6%	-8.5%	-3.4%	12.1%
0.7	9.5%	5.9%	-7.6%	8.7%	-4.5%	2.6%	-25.7%	7.6%	-7.1%	0.3%	14.7%
0.75	14.7%	10.8%	-5.4%	11.1%	-3.5%	4.0%	-23.3%	12.5%	-5.7%	4.1%	17.4%
0.8	16.9%	16.6%	-2.9%	14.2%	-2.0%	5.4%	-21.5%	16.6%	-1.7%	7.6%	20.1%
0.85	19.7%	19.8%	1.6%	17.4%	1.8%	8.0%	-20.0%	22.1%	2.5%	12.0%	22.8%
0.9	22.5%	27.1%	6.6%	20.1%	9.6%	11.0%	-17.6%	30.6%	6.7%	17.8%	25.4%
0.95	25.4%	33.2%	12.4%	21.9%	17.7%	15.4%	-6.4%	39.2%	10.5%	29.5%	28.1%
1	37.5%	50.3%	41.4%	27.1%	26.7%	35.8%	10.6%	48.6%	57.1%	47.7%	30.8%

Table 28. Northeast District Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-16.3%	-43.7%	-2.7%	-17.8%	-27.8%	-15.1%	-17.0%	-11.7%	-31.7%	-7.8%	-9.5%
0.05	-16.3%	-43.7%	-2.7%	-17.8%	-27.7%	-15.1%	-16.3%	-11.7%	-31.3%	-7.8%	-9.5%
0.1	-14.4%	-42.4%	-2.5%	-17.3%	-26.7%	-15.0%	-15.2%	-11.7%	-29.2%	-6.7%	-9.5%
0.15	-14.3%	-39.2%	-2.3%	-16.2%	-25.4%	-12.5%	-12.8%	-11.6%	-27.9%	-5.4%	-9.4%
0.2	-14.2%	-36.1%	-2.0%	-14.4%	-21.5%	-11.4%	-9.9%	-11.6%	-25.6%	-3.9%	-9.1%
0.25	-14.1%	-32.9%	-1.8%	-13.6%	-20.2%	-10.4%	-7.2%	-11.5%	-23.8%	-3.4%	-8.5%
0.3	-12.7%	-29.8%	-1.3%	-12.7%	-17.2%	-7.5%	-5.9%	-10.5%	-20.6%	-2.9%	-7.8%
0.35	-8.3%	-26.6%	-0.8%	-11.7%	-12.6%	-6.6%	-4.9%	-9.4%	-15.6%	-2.3%	-7.2%
0.4	-4.5%	-23.5%	2.8%	-10.8%	-10.1%	-5.5%	-3.8%	-8.8%	-11.2%	-1.6%	-3.3%
0.45	-3.6%	-20.4%	9.2%	-9.7%	-8.2%	-3.4%	-2.6%	-7.6%	-9.6%	-0.4%	-2.1%
0.5	-2.6%	-17.2%	10.3%	-7.3%	-7.0%	-2.7%	-1.2%	-6.4%	-7.3%	1.4%	-1.0%
0.55	-1.7%	-14.4%	11.4%	-4.5%	-5.9%	-1.6%	2.8%	-5.2%	-5.2%	3.8%	0.7%
0.6	-0.8%	-14.3%	12.5%	-0.7%	-4.7%	0.4%	5.1%	-4.3%	-2.8%	8.1%	2.3%
0.65	0.1%	-14.2%	13.5%	1.7%	-3.3%	2.9%	6.2%	-3.5%	0.1%	12.3%	4.0%
0.7	1.1%	-14.0%	14.2%	2.5%	-1.9%	4.5%	7.3%	-2.5%	2.7%	16.6%	5.6%
0.75	1.7%	-13.9%	15.3%	5.8%	-0.9%	5.9%	8.5%	-1.1%	5.0%	20.9%	7.3%
0.8	2.2%	-13.8%	16.7%	8.5%	0.0%	7.4%	9.8%	0.6%	7.3%	26.0%	9.0%
0.85	2.7%	-13.7%	18.1%	11.9%	0.9%	10.1%	11.3%	1.9%	9.2%	31.3%	10.6%
0.9	6.1%	-7.7%	21.1%	16.8%	4.0%	14.2%	12.9%	3.2%	13.9%	36.0%	12.5%
0.95	18.6%	-0.5%	25.1%	25.2%	6.8%	20.5%	14.7%	4.9%	19.9%	40.7%	15.0%
1	57.1%	6.7%	28.6%	39.1%	46.2%	32.9%	17.7%	6.9%	25.9%	45.4%	18.6%

Table 29. Kansas City District Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-31.1%	-45.0%	-24.9%	-27.0%	-29.6%	-43.3%	-34.8%	-38.0%	-23.2%	-27.8%	-25.2%
0.05	-31.1%	-42.4%	-24.9%	-24.6%	-29.3%	-34.8%	-34.7%	-36.6%	-22.4%	-27.5%	-19.9%
0.1	-29.9%	-39.5%	-24.8%	-22.2%	-27.7%	-31.0%	-33.9%	-35.9%	-19.5%	-26.5%	-17.9%
0.15	-28.2%	-39.2%	-24.6%	-21.7%	-25.7%	-28.3%	-33.2%	-35.1%	-16.6%	-25.6%	-14.5%
0.2	-26.8%	-37.5%	-22.9%	-20.9%	-24.3%	-26.8%	-32.1%	-33.9%	-13.5%	-22.0%	-12.6%
0.25	-26.8%	-35.4%	-20.8%	-18.9%	-22.8%	-24.7%	-30.5%	-32.9%	-13.1%	-20.7%	-11.1%
0.3	-26.8%	-33.2%	-18.8%	-17.1%	-21.5%	-22.1%	-28.7%	-32.1%	-12.4%	-19.3%	-9.6%
0.35	-26.5%	-31.1%	-15.7%	-15.7%	-18.9%	-18.0%	-25.0%	-29.1%	-11.6%	-17.5%	-8.2%
0.4	-25.8%	-28.9%	-13.2%	-15.1%	-16.7%	-14.1%	-21.2%	-27.0%	-9.8%	-15.7%	-6.4%
0.45	-25.2%	-27.3%	-11.2%	-13.7%	-14.6%	-10.4%	-18.8%	-25.2%	-7.9%	-13.9%	-4.6%
0.5	-24.5%	-26.9%	-9.3%	-12.4%	-12.1%	-5.6%	-14.3%	-22.5%	-7.0%	-12.1%	-2.8%
0.55	-12.4%	-26.4%	-7.3%	-10.9%	-10.2%	-2.4%	-11.6%	-20.4%	-3.5%	-10.3%	-1.2%
0.6	-2.0%	-26.0%	-5.3%	-8.2%	-7.9%	-1.7%	-9.1%	-18.1%	-0.2%	-7.7%	0.5%
0.65	2.4%	-25.5%	-2.8%	-4.8%	-6.1%	-0.9%	-7.4%	-15.8%	2.6%	-4.2%	2.1%
0.7	6.8%	-23.9%	0.1%	-3.2%	-4.3%	0.4%	-4.4%	-13.3%	6.7%	0.5%	3.8%
0.75	11.4%	-21.2%	3.7%	0.4%	-2.2%	2.0%	-1.9%	-9.8%	10.6%	5.9%	5.7%
0.8	15.9%	-18.8%	7.2%	2.7%	5.2%	7.4%	0.6%	-4.2%	14.6%	10.8%	10.8%
0.85	20.5%	-17.9%	10.7%	4.5%	10.3%	9.6%	3.6%	1.2%	19.6%	14.8%	15.5%
0.9	26.6%	-16.1%	14.2%	6.3%	13.4%	11.6%	6.4%	6.4%	24.9%	17.4%	18.8%
0.95	33.7%	-13.9%	20.0%	9.7%	21.6%	16.0%	10.4%	11.7%	34.1%	20.6%	24.9%
1	57.0%	4.1%	33.3%	22.1%	35.0%	22.1%	28.6%	20.0%	47.6%	26.8%	34.4%

Table 30. Central District Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-20.5%	-30.9%	-28.5%	-29.7%	-34.5%	-27.5%	-32.1%	-43.7%	-46.3%	-26.2%	-33.0%
0.05	-20.5%	-30.9%	-27.4%	-29.5%	-34.1%	-27.3%	-30.1%	-43.5%	-46.2%	-26.2%	-32.7%
0.1	-20.5%	-30.9%	-24.3%	-28.5%	-29.7%	-26.9%	-28.3%	-42.4%	-44.5%	-26.2%	-30.6%
0.15	-20.5%	-30.8%	-21.8%	-26.2%	-28.2%	-21.8%	-27.5%	-38.7%	-43.2%	-26.2%	-28.5%
0.2	-20.5%	-30.6%	-19.0%	-23.1%	-26.9%	-20.1%	-26.7%	-33.7%	-42.0%	-25.9%	-26.2%
0.25	-19.9%	-30.5%	-16.1%	-16.5%	-25.9%	-18.6%	-25.9%	-30.7%	-40.8%	-25.7%	-23.9%
0.3	-19.3%	-30.3%	-13.1%	-13.9%	-24.7%	-17.3%	-24.3%	-25.7%	-38.9%	-25.4%	-21.2%
0.35	-18.7%	-29.7%	-9.7%	-13.0%	-22.3%	-15.7%	-23.0%	-21.5%	-37.5%	-25.2%	-18.3%
0.4	-18.1%	-29.0%	-7.6%	-11.7%	-19.6%	-10.8%	-19.5%	-17.4%	-35.7%	-24.9%	-16.5%
0.45	-17.4%	-28.4%	-6.3%	-10.6%	-14.5%	-9.0%	-15.1%	-14.1%	-31.9%	-24.7%	-15.3%
0.5	-16.8%	-27.7%	-5.2%	-9.8%	-9.1%	-6.3%	-10.4%	-10.5%	-29.5%	-23.7%	-14.1%
0.55	-16.2%	-27.0%	-4.2%	-7.7%	-5.8%	-4.4%	-8.3%	-6.9%	-25.8%	-22.0%	-13.0%
0.6	-10.3%	-26.4%	-3.3%	-4.7%	-4.8%	-2.5%	-6.5%	-4.7%	-20.8%	-19.1%	-10.5%
0.65	-4.4%	-21.9%	-2.6%	-2.1%	-3.5%	-1.0%	-3.1%	-2.6%	-15.4%	-12.7%	-7.5%
0.7	1.5%	-12.5%	-1.2%	0.7%	-2.6%	0.6%	0.2%	-0.6%	-10.0%	-7.1%	-3.6%
0.75	3.6%	-7.5%	0.8%	2.6%	-0.6%	2.8%	2.2%	1.3%	-5.6%	-2.6%	0.6%
0.8	5.2%	-3.8%	2.1%	5.0%	1.1%	5.4%	4.5%	3.2%	-1.8%	2.3%	5.1%
0.85	6.7%	0.2%	3.5%	6.1%	2.7%	8.7%	9.3%	6.3%	1.4%	6.7%	12.2%
0.9	8.3%	4.4%	6.6%	8.4%	7.1%	11.7%	16.7%	10.7%	5.0%	13.3%	19.8%
0.95	9.8%	8.7%	11.5%	13.6%	11.9%	17.2%	23.7%	17.5%	10.5%	19.3%	27.4%
1	11.4%	13.0%	35.3%	22.0%	22.6%	38.3%	34.8%	28.6%	22.4%	25.7%	38.4%

Table 31. St. Louis District Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-22.1%	-27.4%	-50.3%	-26.4%	-34.8%	-12.4%	-32.3%	-40.5%	-40.0%	-33.0%	-37.0%
0.05	-22.1%	-27.4%	-34.0%	-25.8%	-27.6%	-12.4%	-31.5%	-33.9%	-38.6%	-32.4%	-31.0%
0.1	-22.1%	-27.3%	-31.4%	-23.4%	-26.2%	-12.0%	-29.3%	-32.8%	-34.9%	-30.7%	-26.0%
0.15	-22.1%	-27.1%	-29.8%	-17.8%	-25.0%	-11.6%	-25.4%	-27.7%	-28.0%	-28.5%	-18.1%
0.2	-22.1%	-26.6%	-29.1%	-14.2%	-23.0%	-11.1%	-21.6%	-26.8%	-20.3%	-27.0%	-13.5%
0.25	-22.1%	-26.2%	-28.3%	-11.2%	-20.2%	-10.4%	-17.4%	-25.1%	-15.7%	-25.4%	-11.1%
0.3	-22.0%	-25.7%	-26.0%	-9.1%	-17.4%	-9.3%	-15.0%	-23.6%	-12.7%	-23.6%	-7.7%
0.35	-20.9%	-25.3%	-24.9%	-7.0%	-14.7%	-8.3%	-12.6%	-22.2%	-10.0%	-21.2%	-4.3%
0.4	-19.8%	-24.8%	-24.1%	-6.3%	-12.5%	-7.2%	-11.4%	-20.8%	-7.7%	-18.5%	4.5%
0.45	-18.3%	-23.9%	-22.7%	-5.7%	-10.3%	-6.2%	-8.7%	-19.5%	-5.6%	-15.5%	5.8%
0.5	-16.8%	-22.0%	-21.3%	-5.0%	-7.4%	-5.3%	-6.4%	-18.3%	-1.7%	-12.8%	6.4%
0.55	-15.1%	-20.0%	-19.9%	-3.8%	-6.0%	-4.3%	-4.8%	-16.8%	1.3%	-8.6%	7.1%
0.6	-14.0%	-17.2%	-16.2%	-2.1%	-4.6%	-3.2%	-1.6%	-15.2%	4.0%	-3.7%	9.5%
0.65	-13.3%	-13.5%	-13.0%	-0.3%	-3.2%	-2.1%	3.3%	-13.8%	6.5%	-1.9%	11.0%
0.7	-12.6%	-9.6%	-11.1%	1.1%	-1.8%	-1.0%	6.2%	-11.7%	8.8%	-0.2%	11.6%
0.75	-11.8%	-5.7%	-9.0%	2.2%	-0.4%	0.1%	7.3%	-8.8%	11.1%	1.6%	12.3%
0.8	-11.1%	-1.9%	-4.8%	3.7%	3.2%	1.2%	8.4%	-4.4%	14.6%	3.4%	12.9%
0.85	-10.0%	2.4%	-1.7%	5.5%	9.1%	3.3%	9.5%	1.6%	17.9%	5.6%	14.8%
0.9	-8.7%	7.2%	1.6%	10.3%	17.0%	7.1%	14.3%	6.5%	22.8%	8.5%	17.2%
0.95	-7.4%	12.1%	7.1%	15.2%	25.1%	9.5%	20.6%	11.3%	29.6%	16.0%	21.8%
1	13.1%	17.9%	22.3%	23.9%	38.5%	23.9%	24.9%	23.3%	38.9%	34.5%	43.5%

Table 32. Southwest District Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-3.9%	-15.1%	-28.0%	-37.2%	-33.3%	-23.7%	-19.2%	-45.9%	-27.7%	-24.0%	-32.1%
0.05	-3.9%	-9.4%	-26.0%	-35.5%	-31.2%	-22.7%	-18.5%	-38.7%	-27.6%	-23.3%	-29.8%
0.1	-3.9%	-8.0%	-22.6%	-34.4%	-29.0%	-20.2%	-16.0%	-31.6%	-26.6%	-21.3%	-26.4%
0.15	-3.9%	-6.4%	-19.3%	-33.1%	-27.3%	-16.4%	-13.2%	-30.0%	-25.6%	-14.5%	-21.7%
0.2	-3.9%	-5.7%	-16.8%	-30.6%	-26.3%	-14.8%	-10.9%	-28.4%	-24.8%	-13.0%	-17.9%
0.25	1.6%	-5.3%	-15.0%	-27.7%	-24.6%	-12.4%	-9.3%	-26.7%	-23.9%	-11.1%	-14.6%
0.3	6.2%	-4.9%	-13.4%	-25.8%	-22.9%	-10.3%	-7.8%	-25.3%	-21.3%	-5.7%	-11.9%
0.35	7.2%	-3.4%	-12.3%	-23.9%	-21.5%	-9.4%	-6.4%	-19.7%	-18.6%	-0.3%	-9.2%
0.4	8.2%	-1.5%	-10.0%	-22.1%	-20.2%	-8.4%	-5.5%	-16.7%	-15.8%	2.0%	-5.1%
0.45	9.5%	0.9%	-8.6%	-20.1%	-19.1%	-7.5%	-4.3%	-14.1%	-14.2%	4.0%	-0.7%
0.5	10.7%	3.3%	-6.4%	-19.0%	-18.1%	-6.5%	-2.3%	-13.3%	-13.3%	5.1%	3.4%
0.55	12.1%	4.6%	-4.9%	-18.0%	-14.1%	-5.4%	-1.5%	-11.5%	-12.4%	6.1%	7.8%
0.6	13.5%	5.2%	-3.2%	-17.0%	-12.5%	-3.8%	-0.8%	-6.4%	-11.1%	8.2%	10.6%
0.65	15.0%	5.9%	-2.2%	-15.2%	-11.1%	-1.7%	0.9%	-4.6%	-7.9%	10.2%	13.1%
0.7	20.2%	6.8%	-0.3%	-11.8%	-7.7%	0.5%	2.5%	-1.6%	-4.2%	13.9%	15.6%
0.75	27.4%	7.5%	3.4%	-9.0%	-4.2%	2.6%	6.0%	0.8%	0.1%	15.7%	17.6%
0.8	31.8%	8.2%	6.1%	-5.5%	-2.3%	5.6%	9.3%	3.8%	4.5%	17.5%	21.4%
0.85	35.0%	10.9%	7.2%	-2.2%	2.0%	8.7%	13.5%	8.7%	7.9%	20.9%	28.8%
0.9	38.2%	15.8%	8.1%	0.7%	6.8%	11.9%	20.3%	17.1%	11.5%	23.9%	32.3%
0.95	41.4%	19.1%	9.5%	6.4%	11.9%	15.9%	29.4%	25.2%	15.5%	27.2%	35.5%
1	44.6%	28.5%	27.9%	19.3%	19.3%	29.2%	45.5%	55.4%	26.4%	30.3%	49.6%

Table 33. Southeast District Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-21.8%	-2.0%	-17.3%	-21.9%	-20.3%	-17.7%	-34.8%	-17.2%	-28.3%	-22.8%	-43.2%
0.05	-21.8%	-2.0%	-17.3%	-21.4%	-20.0%	-17.5%	-31.5%	-17.2%	-28.3%	-22.8%	-36.0%
0.1	-21.8%	-2.0%	-16.8%	-20.2%	-16.8%	-17.0%	-22.6%	-16.7%	-28.2%	-22.8%	-33.8%
0.15	-21.6%	-2.0%	-16.0%	-18.8%	-15.2%	-16.1%	-18.4%	-13.6%	-24.1%	-22.7%	-31.5%
0.2	-21.5%	-2.0%	-15.0%	-16.5%	-14.1%	-13.7%	-15.9%	-12.9%	-19.0%	-22.1%	-28.9%
0.25	-21.3%	-2.0%	-14.0%	-15.1%	-13.0%	-10.3%	-14.9%	-11.8%	-16.9%	-21.3%	-25.5%
0.3	-21.2%	-2.0%	-13.2%	-13.9%	-11.7%	-8.6%	-14.0%	-8.3%	-15.2%	-20.4%	-23.4%
0.35	-21.0%	-2.0%	-11.7%	-12.5%	-9.7%	-5.8%	-10.7%	-6.2%	-12.8%	-16.8%	-21.9%
0.4	-14.0%	-2.0%	-10.2%	-10.6%	-7.3%	-3.9%	-9.8%	-4.0%	-10.6%	-12.3%	-19.4%
0.45	-6.5%	-2.0%	-8.7%	-8.0%	-6.8%	-2.7%	-9.0%	-2.0%	-8.6%	-7.7%	-13.1%
0.5	1.0%	-2.0%	-7.2%	-6.5%	-6.1%	-1.6%	-6.4%	-0.7%	-7.4%	-4.2%	-10.4%
0.55	5.0%	-2.0%	-5.8%	-5.4%	-5.2%	-0.4%	-5.9%	0.9%	-6.1%	-1.9%	-8.8%
0.6	5.3%	-2.0%	-4.5%	-3.4%	-4.0%	1.2%	-4.0%	2.7%	-1.5%	-0.2%	-7.5%
0.65	5.5%	-2.0%	-3.8%	-1.8%	-2.2%	2.6%	-1.6%	4.4%	1.4%	1.8%	-4.8%
0.7	5.7%	-2.0%	-3.2%	-0.4%	-0.7%	5.4%	3.1%	6.1%	3.7%	3.9%	-0.1%
0.75	6.9%	5.6%	-2.5%	2.0%	1.3%	8.1%	8.0%	7.8%	5.4%	6.2%	5.9%
0.8	9.2%	13.2%	-1.6%	4.1%	3.6%	13.0%	11.5%	9.8%	8.2%	8.7%	11.5%
0.85	11.6%	23.0%	0.0%	5.3%	5.1%	17.0%	14.4%	11.8%	16.3%	12.0%	15.9%
0.9	13.9%	33.2%	1.6%	10.6%	7.0%	21.1%	21.1%	14.1%	24.8%	17.8%	20.1%
0.95	16.2%	44.7%	4.5%	16.8%	11.8%	26.9%	27.4%	17.6%	32.2%	22.9%	25.9%
1	18.6%	56.2%	15.6%	29.0%	20.2%	49.1%	44.0%	24.0%	43.5%	28.1%	45.4%

A.3. Project Type Performance Curves and Heatmaps

Project type performance curves are shown in Figure 35 and heatmaps are shown in Table 34 through Table 38. The tables do indicate that the signal and SSGL project type data does get thin enough where curves cannot be produced for each month. This is simply a result of not many projects of those types being let in those months. Generally, the curves indicate that:

- Paving projects have the most success November and January through March, with highest prices in April and May
- Bridge projects have the most success August through December and February through May if total monthly let values are not high.

Figure 35. Project Type Month Performance Curves

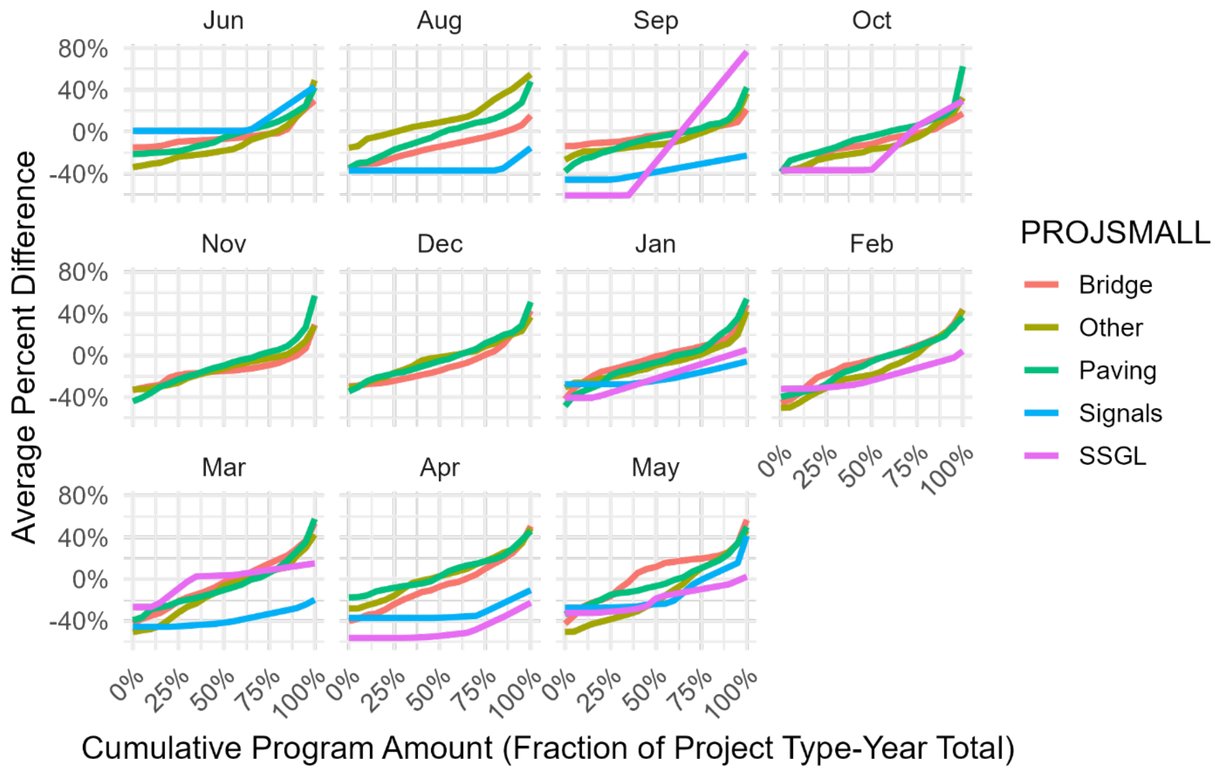

Table 34. Paving Project Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-21.3%	-34.8%	-38.0%	-38.7%	-44.0%	-34.5%	-48.5%	-39.6%	-39.4%	-17.7%	-34.0%
0.05	-21.1%	-30.1%	-30.5%	-27.5%	-40.5%	-30.4%	-38.3%	-37.7%	-36.7%	-17.2%	-29.7%
0.1	-20.3%	-29.2%	-25.8%	-24.7%	-35.8%	-24.6%	-34.3%	-36.0%	-28.9%	-15.6%	-27.1%
0.15	-19.8%	-25.3%	-24.0%	-22.1%	-30.1%	-21.2%	-30.9%	-33.5%	-26.9%	-11.8%	-23.2%
0.2	-19.2%	-21.4%	-20.2%	-20.0%	-26.8%	-19.3%	-27.3%	-31.8%	-25.2%	-10.0%	-19.6%
0.25	-18.6%	-16.9%	-18.0%	-17.3%	-23.0%	-17.2%	-19.1%	-27.6%	-21.6%	-8.3%	-15.1%
0.3	-16.6%	-14.2%	-14.7%	-14.9%	-20.0%	-15.9%	-15.5%	-20.7%	-19.8%	-6.8%	-13.3%
0.35	-14.0%	-11.5%	-11.5%	-11.2%	-17.8%	-13.4%	-13.5%	-15.9%	-18.0%	-5.6%	-12.5%
0.4	-12.2%	-8.5%	-9.0%	-7.9%	-14.5%	-10.6%	-11.5%	-13.2%	-15.7%	-4.2%	-11.1%
0.45	-9.9%	-5.8%	-7.0%	-6.0%	-11.8%	-8.0%	-8.9%	-10.2%	-13.3%	-2.2%	-8.6%
0.5	-5.4%	-1.5%	-5.1%	-4.0%	-9.7%	-5.3%	-6.7%	-5.6%	-10.6%	2.6%	-6.7%
0.55	-2.8%	1.8%	-3.4%	-1.9%	-6.5%	-3.4%	-4.6%	-2.1%	-8.0%	7.6%	-4.6%
0.6	0.0%	3.4%	-2.2%	0.6%	-4.1%	0.2%	-0.5%	0.6%	-5.1%	10.7%	-0.9%
0.65	2.4%	6.2%	-0.5%	2.5%	-2.5%	3.2%	1.3%	3.1%	-0.4%	13.1%	1.6%
0.7	4.6%	8.7%	1.2%	4.2%	0.9%	6.2%	2.9%	4.6%	1.5%	14.7%	7.1%
0.75	6.9%	10.1%	3.6%	6.0%	3.3%	11.8%	5.6%	8.2%	6.0%	17.2%	10.6%
0.8	9.9%	12.7%	7.2%	9.6%	5.3%	15.2%	11.7%	12.0%	10.7%	19.1%	14.3%
0.85	14.3%	16.4%	8.0%	13.5%	8.9%	19.6%	19.4%	14.9%	17.6%	22.4%	18.1%
0.9	19.4%	21.4%	12.0%	15.7%	16.0%	22.1%	25.6%	18.9%	26.4%	29.1%	24.1%
0.95	25.0%	27.9%	22.5%	22.8%	26.8%	28.6%	35.5%	28.3%	35.4%	37.3%	34.5%
1	42.7%	48.3%	42.7%	62.7%	57.2%	51.2%	54.2%	36.6%	57.7%	46.0%	50.1%

Table 35. Bridge Project Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-15.0%	-36.0%	-13.6%	-37.2%	-33.4%	-29.6%	-42.0%	-45.3%	-42.2%	-40.1%	-42.7%
0.05	-15.0%	-31.0%	-13.6%	-36.2%	-31.0%	-28.9%	-31.4%	-42.6%	-38.2%	-38.1%	-35.0%
0.1	-14.4%	-30.7%	-12.4%	-34.9%	-29.4%	-27.5%	-25.6%	-36.3%	-35.2%	-34.4%	-26.4%
0.15	-13.8%	-30.3%	-11.0%	-33.2%	-28.1%	-26.7%	-19.9%	-28.1%	-32.4%	-32.9%	-22.4%
0.2	-11.6%	-27.9%	-10.6%	-26.4%	-21.3%	-25.9%	-15.6%	-21.0%	-27.2%	-29.2%	-20.0%
0.25	-9.4%	-24.8%	-10.0%	-19.8%	-18.7%	-24.2%	-13.7%	-17.7%	-21.1%	-23.9%	-16.7%
0.3	-9.0%	-22.3%	-9.4%	-16.5%	-17.4%	-22.4%	-11.5%	-14.5%	-17.5%	-19.7%	-9.1%
0.35	-8.5%	-20.3%	-8.0%	-15.3%	-17.1%	-20.7%	-8.9%	-10.0%	-14.7%	-16.3%	-2.7%
0.4	-8.1%	-18.0%	-6.6%	-14.1%	-15.9%	-18.6%	-6.6%	-8.7%	-11.8%	-12.5%	5.9%
0.45	-7.4%	-15.9%	-4.4%	-12.9%	-15.5%	-16.9%	-4.0%	-6.7%	-8.1%	-10.8%	9.7%
0.5	-6.7%	-14.2%	-3.6%	-11.7%	-15.0%	-14.5%	-0.8%	-4.3%	-3.1%	-7.1%	11.6%
0.55	-6.0%	-12.5%	-2.4%	-8.8%	-14.5%	-11.4%	0.5%	-2.0%	0.5%	-4.3%	15.5%
0.6	-5.5%	-10.6%	-1.1%	-6.1%	-13.5%	-9.5%	3.1%	0.0%	2.8%	-2.9%	16.6%
0.65	-4.3%	-8.7%	0.2%	-4.6%	-12.5%	-7.0%	4.7%	3.0%	6.6%	0.7%	17.8%
0.7	-3.2%	-6.8%	1.4%	-3.1%	-10.9%	-3.3%	6.4%	6.4%	10.8%	4.4%	18.9%
0.75	-2.0%	-5.0%	2.8%	-1.6%	-9.3%	0.6%	8.8%	9.2%	14.9%	10.0%	19.6%
0.8	-1.2%	-2.8%	4.2%	0.7%	-7.3%	4.0%	10.7%	12.6%	18.7%	14.8%	21.0%
0.85	2.7%	-0.4%	5.6%	2.9%	-3.7%	10.7%	13.7%	16.4%	22.6%	19.2%	22.6%
0.9	14.5%	2.5%	7.2%	8.1%	-0.2%	21.4%	17.1%	20.3%	29.1%	25.0%	25.9%
0.95	22.4%	6.3%	9.4%	12.1%	6.7%	26.4%	27.4%	30.0%	36.7%	34.1%	34.2%
1	29.9%	15.4%	21.4%	17.6%	29.6%	43.0%	48.6%	43.9%	53.5%	50.7%	56.8%

Table 36. Signing Striping Guardrail and Lighting Project Heatmap

Percentile	Sep	Oct	Jan	Feb	Mar	Apr	May
0	-60.9%	-36.7%	-40.5%	-32.0%	-26.8%	-56.4%	-32.4%
0.05	-60.9%	-36.7%	-40.5%	-32.0%	-26.8%	-56.4%	-32.4%
0.1	-60.9%	-36.7%	-40.5%	-32.0%	-26.8%	-56.4%	-32.4%
0.15	-60.9%	-36.7%	-40.5%	-31.7%	-22.7%	-56.4%	-32.4%
0.2	-60.9%	-36.7%	-38.4%	-31.4%	-15.9%	-56.4%	-31.9%
0.25	-60.9%	-36.7%	-35.7%	-30.7%	-9.1%	-56.4%	-31.2%
0.3	-60.9%	-36.7%	-33.0%	-29.9%	-2.4%	-56.4%	-30.5%
0.35	-60.8%	-36.7%	-30.2%	-29.1%	2.6%	-56.2%	-29.7%
0.4	-50.2%	-36.7%	-27.5%	-28.1%	2.9%	-55.7%	-28.3%
0.45	-39.6%	-36.7%	-24.7%	-26.3%	3.1%	-55.3%	-25.8%
0.5	-29.0%	-36.3%	-22.0%	-23.9%	3.4%	-54.4%	-18.6%
0.55	-18.5%	-27.8%	-19.3%	-21.5%	3.7%	-53.4%	-15.8%
0.6	-7.9%	-19.4%	-16.5%	-19.1%	4.9%	-52.5%	-14.3%
0.65	2.7%	-10.9%	-13.8%	-16.7%	6.2%	-51.5%	-12.7%
0.7	13.3%	-2.5%	-11.0%	-14.3%	7.5%	-48.3%	-11.2%
0.75	23.9%	5.6%	-8.3%	-11.9%	8.7%	-44.2%	-9.7%
0.8	34.4%	10.4%	-5.5%	-9.5%	10.0%	-40.2%	-8.1%
0.85	45.0%	15.2%	-2.8%	-7.1%	11.2%	-36.3%	-6.6%
0.9	55.6%	20.0%	-0.1%	-4.7%	12.5%	-31.7%	-5.1%
0.95	66.2%	24.8%	2.7%	-2.2%	13.8%	-27.2%	-1.4%
1	76.7%	29.6%	5.4%	4.1%	15.0%	-22.6%	2.2%

Table 37. Signal Project Heatmap

Percentile	Jun	Aug	Sep	Jan	Mar	Apr	May
0	0.9%	-37.1%	-45.8%	-27.5%	-45.7%	-37.2%	-27.4%
0.05	0.9%	-37.1%	-45.8%	-27.5%	-45.7%	-37.2%	-27.4%
0.1	0.9%	-37.1%	-45.8%	-27.5%	-45.7%	-37.2%	-27.4%
0.15	0.9%	-37.1%	-45.8%	-27.5%	-45.7%	-37.2%	-27.4%
0.2	0.9%	-37.1%	-45.8%	-27.5%	-45.7%	-37.2%	-27.4%
0.25	0.9%	-37.1%	-45.8%	-27.5%	-45.2%	-37.2%	-27.2%
0.3	0.9%	-37.1%	-44.9%	-27.5%	-44.7%	-37.2%	-27.0%
0.35	0.9%	-37.1%	-43.3%	-27.5%	-44.1%	-37.2%	-26.8%
0.4	0.9%	-37.1%	-41.7%	-26.6%	-43.5%	-37.2%	-26.1%
0.45	0.9%	-37.1%	-40.1%	-25.3%	-42.9%	-37.2%	-24.5%
0.5	0.9%	-37.1%	-38.6%	-24.1%	-41.7%	-37.0%	-24.1%
0.55	0.9%	-37.1%	-37.0%	-22.9%	-40.6%	-36.6%	-23.6%
0.6	0.9%	-37.1%	-35.4%	-21.6%	-38.7%	-36.2%	-20.6%
0.65	2.1%	-37.1%	-33.8%	-19.8%	-36.9%	-35.7%	-13.4%
0.7	7.9%	-37.1%	-32.2%	-17.9%	-35.1%	-35.3%	-5.6%
0.75	13.7%	-37.1%	-30.7%	-16.0%	-33.3%	-31.3%	-0.7%
0.8	19.6%	-37.1%	-29.1%	-14.1%	-31.5%	-27.2%	3.3%
0.85	25.5%	-34.9%	-27.5%	-12.1%	-29.7%	-23.0%	7.4%
0.9	31.4%	-28.4%	-25.9%	-10.0%	-27.9%	-18.9%	11.4%
0.95	37.3%	-21.9%	-24.4%	-7.9%	-24.4%	-14.7%	15.4%
1	43.2%	-15.4%	-22.8%	-5.8%	-19.8%	-10.6%	41.4%

Table 38. Other Project Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-33.8%	-15.3%	-26.9%	-37.3%	-32.4%	-30.7%	-30.8%	-50.1%	-50.7%	-28.2%	-50.5%
0.05	-32.4%	-13.7%	-22.2%	-36.7%	-32.3%	-29.4%	-26.3%	-49.7%	-49.1%	-28.2%	-50.3%
0.1	-30.8%	-6.7%	-19.0%	-34.7%	-31.6%	-25.9%	-26.1%	-45.3%	-47.9%	-25.2%	-46.5%
0.15	-29.7%	-4.7%	-18.8%	-31.1%	-29.8%	-22.5%	-24.9%	-39.7%	-44.7%	-22.7%	-42.9%
0.2	-27.0%	-2.6%	-18.3%	-27.1%	-28.1%	-20.8%	-22.0%	-35.2%	-38.7%	-19.9%	-40.8%
0.25	-24.0%	-0.3%	-17.1%	-25.2%	-26.2%	-16.5%	-20.8%	-31.1%	-32.1%	-15.7%	-38.6%
0.3	-23.0%	2.1%	-16.1%	-23.3%	-21.8%	-13.8%	-19.2%	-25.7%	-26.5%	-9.4%	-36.1%
0.35	-22.0%	4.5%	-15.0%	-22.1%	-19.0%	-10.2%	-17.5%	-22.9%	-23.3%	-3.7%	-33.6%
0.4	-21.0%	6.1%	-13.9%	-20.9%	-16.7%	-4.8%	-14.6%	-21.4%	-17.6%	-1.4%	-30.8%
0.45	-19.6%	7.5%	-12.8%	-19.6%	-14.7%	-2.8%	-13.0%	-20.0%	-13.4%	0.2%	-26.0%
0.5	-18.1%	9.1%	-12.3%	-16.6%	-12.7%	-1.6%	-9.4%	-18.7%	-6.5%	2.8%	-22.8%
0.55	-16.7%	10.9%	-11.6%	-15.7%	-9.6%	-0.3%	-7.3%	-15.7%	-3.7%	5.0%	-15.9%
0.6	-13.1%	12.5%	-9.9%	-14.5%	-7.8%	1.0%	-6.0%	-10.7%	-1.8%	7.4%	-10.2%
0.65	-7.6%	14.4%	-7.6%	-12.2%	-6.0%	3.0%	-4.1%	-7.5%	2.0%	9.9%	-4.7%
0.7	-4.8%	18.2%	-4.1%	-8.4%	-4.5%	4.3%	-1.4%	-3.1%	5.7%	14.2%	3.7%
0.75	-2.0%	24.6%	-1.1%	-5.2%	-2.8%	8.9%	1.0%	1.6%	7.8%	17.2%	10.4%
0.8	0.8%	31.1%	2.1%	-0.3%	-1.2%	11.4%	5.1%	9.9%	9.6%	20.9%	14.6%
0.85	6.2%	36.4%	5.7%	7.0%	1.1%	17.3%	8.5%	15.4%	11.4%	25.3%	19.5%
0.9	14.6%	41.1%	10.2%	14.1%	6.5%	20.3%	11.6%	21.7%	22.1%	28.3%	25.8%
0.95	23.9%	48.0%	17.6%	18.5%	13.6%	23.3%	19.9%	27.1%	29.8%	34.0%	33.8%
1	49.5%	55.1%	36.8%	32.8%	28.3%	37.0%	42.3%	43.7%	42.7%	48.7%	46.8%

A.4. District + Project Type Performance Curves

While not explicitly used in the optimization analysis, district + project type performance curves were developed as a reference given the finding that the optimization approach using separate district and project type curves indicated that idea timing was often out of alignment, resulting in higher optimization costs than base monthly distributions. These curves can be used by districts if more manually let planning practices are being used to leverage findings from this research in targeting project type lettings. Heatmaps that are missing months did not have enough observations to produce a performance curve. Reminder that missing months from the heatmaps indicate that there were several years of historical data did not have more than one project per district + project type + month group and thus could not be interpolated.

Table 39. Northwest District Paving Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-11.7%	0.1%	-31.5%	-5.5%	-16.9%	-6.3%	-64.1%	-4.8%	-15.5%	-11.7%	-1.4%
0.05	-11.7%	0.2%	-31.4%	-5.5%	-16.9%	-6.3%	-64.1%	-4.8%	-15.5%	-11.7%	-1.4%
0.1	-11.7%	0.5%	-27.6%	-5.4%	-16.9%	-5.7%	-64.1%	-4.8%	-15.5%	-11.7%	-1.4%
0.15	-11.7%	0.9%	-25.9%	-5.3%	-16.5%	-4.3%	-63.9%	-4.8%	-15.5%	-11.7%	-1.4%
0.2	-11.6%	1.3%	-24.1%	-5.1%	-16.0%	-2.6%	-53.0%	-4.8%	-15.3%	-11.7%	-1.4%
0.25	-11.5%	1.5%	-22.1%	-4.8%	-11.2%	-1.9%	-49.2%	-4.8%	-14.9%	-11.4%	0.8%
0.3	-11.0%	1.6%	-20.1%	-4.0%	-10.3%	-1.2%	-46.8%	-4.8%	-14.4%	-10.9%	4.3%
0.35	-9.9%	1.7%	-18.4%	-2.5%	-9.1%	-0.2%	-44.3%	-4.8%	-13.9%	-10.5%	7.7%
0.4	-8.8%	1.9%	-17.6%	-0.9%	-8.0%	0.8%	-41.9%	-4.8%	-13.4%	-10.0%	11.1%
0.45	-7.5%	2.2%	-16.7%	0.9%	-6.0%	2.9%	-39.4%	-4.8%	-12.9%	-9.5%	14.5%
0.5	-5.7%	3.2%	-15.0%	3.2%	-4.9%	4.9%	-37.2%	-4.2%	-12.4%	-9.1%	17.9%
0.55	-3.0%	4.7%	-13.5%	5.8%	-4.5%	6.2%	-36.1%	-3.5%	-11.9%	-6.2%	21.3%
0.6	-0.5%	6.3%	-11.9%	10.1%	-4.0%	8.6%	-35.0%	-2.8%	-11.4%	-3.2%	24.7%
0.65	1.4%	8.3%	-10.4%	13.3%	-3.6%	11.0%	-34.0%	1.1%	-10.3%	-0.2%	28.8%
0.7	2.6%	10.6%	-7.4%	14.9%	-3.1%	13.5%	-32.9%	6.1%	-8.6%	2.8%	33.4%
0.75	3.8%	14.3%	-4.1%	16.5%	-2.0%	15.8%	-32.5%	10.8%	-6.9%	5.8%	38.1%
0.8	5.7%	18.5%	0.3%	18.0%	-0.7%	18.0%	-30.8%	14.9%	-5.1%	8.8%	42.7%
0.85	9.2%	23.4%	5.3%	19.6%	3.4%	20.3%	-26.3%	19.0%	-3.4%	15.6%	47.3%
0.9	13.5%	27.7%	11.0%	21.2%	12.1%	22.6%	-17.7%	23.1%	-1.6%	28.7%	52.0%
0.95	18.2%	32.9%	16.6%	22.8%	18.4%	27.6%	-7.2%	27.2%	0.1%	41.8%	56.6%
1	23.1%	55.7%	21.6%	24.4%	25.8%	42.3%	16.0%	31.3%	1.9%	54.9%	61.2%

Table 40. Northwest District Bridge Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	May
0	-5.4%	-36.4%	-3.9%	-12.8%	-19.6%	-17.8%	-48.8%	-10.2%	-3.8%	-15.1%
0.05	-5.4%	-36.4%	-3.9%	-12.8%	-19.6%	-17.8%	-48.8%	-10.2%	-3.8%	-15.1%
0.1	-5.4%	-36.4%	-3.9%	-12.8%	-19.6%	-17.8%	-48.8%	-10.2%	-3.8%	-15.1%
0.15	-5.4%	-35.7%	-3.9%	-12.8%	-19.6%	-17.8%	-48.8%	-10.2%	-3.8%	-15.1%
0.2	-5.4%	-33.5%	-3.8%	-12.8%	-19.6%	-17.8%	-48.2%	-9.2%	-3.8%	-15.1%
0.25	-5.4%	-31.4%	-3.7%	-12.8%	-19.6%	-17.8%	-47.7%	-7.2%	-3.8%	-15.1%
0.3	-5.4%	-29.2%	-3.6%	-12.8%	-19.6%	-17.8%	-47.7%	-5.3%	-3.8%	-15.1%
0.35	-5.4%	-27.0%	-3.5%	-12.8%	-19.6%	-17.8%	-46.6%	-3.4%	-3.6%	-15.1%
0.4	-5.4%	-24.3%	-3.3%	-12.8%	-19.6%	-17.8%	-44.6%	-1.2%	-3.4%	-15.1%
0.45	-4.7%	-21.6%	-3.1%	-12.8%	-19.6%	-17.8%	-42.1%	4.5%	-3.2%	-14.2%
0.5	-3.8%	-18.9%	-2.8%	-12.8%	-19.6%	-17.8%	-40.7%	11.4%	-2.9%	-11.5%
0.55	-3.0%	-16.1%	-2.4%	-12.8%	-19.6%	-17.8%	-39.3%	12.7%	-2.7%	-8.8%
0.6	-2.2%	-7.8%	-2.1%	-12.8%	-19.6%	-17.8%	-37.8%	14.1%	-2.5%	-6.1%
0.65	-1.4%	0.6%	6.6%	-12.8%	-19.6%	-17.8%	-36.1%	15.4%	-2.3%	-3.3%
0.7	-0.3%	2.4%	11.2%	-7.5%	-19.5%	-17.8%	-33.7%	16.8%	-2.0%	-0.6%
0.75	2.4%	4.5%	13.8%	5.8%	-3.1%	-17.8%	-31.1%	18.1%	-1.8%	2.1%
0.8	5.3%	6.7%	16.3%	19.1%	-2.2%	-17.8%	-28.7%	19.5%	8.9%	4.8%
0.85	8.1%	8.9%	18.9%	30.2%	1.4%	-10.4%	-23.8%	20.9%	20.3%	7.5%
0.9	10.9%	11.8%	21.5%	31.7%	6.4%	-0.6%	-17.6%	22.2%	31.6%	10.2%
0.95	13.8%	19.0%	24.1%	33.3%	11.3%	9.1%	-11.5%	24.4%	41.8%	12.9%
1	16.6%	27.2%	26.6%	34.8%	15.3%	18.9%	-6.1%	29.2%	42.2%	15.6%

Table 41. Northeast District Paving Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Mar
0	-35.1%	-14.4%	-17.5%	-17.8%	-24.9%	-15.8%	-44.2%	-16.2%
0.05	-35.1%	-14.4%	-17.5%	-17.8%	-24.9%	-15.8%	-41.2%	-16.2%
0.1	-35.1%	-14.4%	-17.5%	-17.8%	-24.9%	-15.7%	-37.2%	-16.2%
0.15	-35.1%	-14.4%	-17.3%	-17.8%	-24.8%	-15.6%	-35.2%	-16.2%
0.2	-35.1%	-14.4%	-17.0%	-17.3%	-24.0%	-11.9%	-33.1%	-16.2%
0.25	-35.1%	-14.4%	-16.8%	-16.6%	-22.3%	-10.3%	-31.0%	-16.2%
0.3	-35.1%	-14.4%	-16.5%	-15.9%	-18.0%	-8.9%	-28.9%	-16.2%
0.35	-35.1%	-14.4%	-16.2%	-14.9%	-13.4%	-6.8%	-26.9%	-16.2%
0.4	-34.4%	-14.4%	-15.9%	-13.8%	-10.8%	-5.5%	-24.8%	-16.2%
0.45	-31.5%	-14.4%	-15.6%	-12.4%	-8.2%	-4.5%	-5.5%	-16.2%
0.5	-28.8%	-14.4%	-15.3%	-11.0%	-6.6%	-2.3%	-3.0%	-16.2%
0.55	-26.3%	-14.3%	-13.7%	-8.7%	-5.1%	0.0%	-0.6%	-16.2%
0.6	-23.7%	-14.2%	-12.0%	-4.6%	-3.6%	1.3%	1.9%	-16.2%
0.65	-21.2%	-14.1%	-6.9%	-0.7%	-1.7%	2.9%	4.3%	-16.2%
0.7	-18.7%	-14.0%	-1.9%	0.3%	0.0%	3.9%	6.8%	-16.2%
0.75	-16.2%	-13.9%	1.9%	1.4%	1.1%	5.0%	9.2%	-16.2%
0.8	-13.7%	-13.8%	5.6%	2.5%	2.3%	6.0%	11.7%	-16.2%
0.85	-11.5%	-13.2%	9.4%	4.7%	3.4%	8.6%	14.1%	-16.2%
0.9	-10.2%	-6.6%	13.2%	10.1%	7.8%	13.1%	16.6%	-5.0%
0.95	-9.0%	0.1%	16.9%	15.7%	11.7%	17.5%	19.0%	15.1%
1	-7.7%	6.7%	20.7%	21.4%	30.6%	31.7%	21.5%	35.2%

Table 42. Northeast District Bridge Heatmap

Percentile	Jun	Dec	Jan	Feb	Mar	Apr	May
0	-18.0%	7.9%	-5.2%	-11.7%	-37.0%	-11.2%	-22.4%
0.05	-18.0%	7.9%	-5.2%	-11.7%	-37.0%	-11.2%	-22.4%
0.1	-18.0%	7.9%	-4.7%	-11.7%	-36.2%	-11.0%	-22.1%
0.15	-18.0%	7.9%	-2.1%	-11.6%	-34.6%	-10.0%	-21.4%
0.2	-18.0%	7.9%	-1.2%	-11.6%	-32.9%	-9.0%	-20.3%
0.25	-18.0%	7.9%	-1.1%	-11.6%	-31.4%	-8.0%	-19.2%
0.3	-14.1%	7.9%	-1.1%	-11.1%	-31.0%	-6.9%	-18.1%
0.35	-1.2%	7.9%	-0.8%	-10.2%	-29.6%	-5.6%	-17.0%
0.4	10.1%	7.9%	-0.3%	-9.2%	-27.1%	-4.4%	-15.9%
0.45	12.7%	7.9%	0.3%	-7.7%	-25.5%	-3.3%	-14.8%
0.5	15.2%	7.9%	0.9%	-6.1%	-24.5%	-2.4%	-13.7%
0.55	17.7%	7.9%	1.7%	-4.9%	-23.1%	-1.4%	-12.5%
0.6	20.3%	8.1%	2.5%	-3.2%	-20.4%	3.0%	-11.4%
0.65	22.8%	8.7%	3.3%	-1.4%	-17.5%	7.5%	-10.3%
0.7	25.3%	9.9%	4.1%	-0.2%	-13.6%	12.0%	-9.2%
0.75	26.8%	11.0%	4.9%	0.8%	-8.4%	16.5%	-8.1%
0.8	28.2%	12.2%	5.7%	1.8%	-3.2%	21.0%	-7.0%
0.85	29.5%	13.3%	6.8%	2.8%	1.3%	23.4%	-5.2%
0.9	30.8%	14.5%	8.1%	4.1%	5.3%	25.4%	-3.0%
0.95	32.1%	15.6%	9.5%	5.5%	9.3%	27.4%	-0.8%
1	33.4%	16.8%	10.8%	6.9%	13.4%	29.5%	1.4%

Table 43. Kansas City District Paving Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-0.8%	-45.4%	-23.2%	-28.1%	-29.6%	-41.1%	-35.9%	-33.8%	-2.0%	-30.7%	3.8%
0.05	-0.8%	-45.4%	-23.2%	-26.4%	-29.6%	-40.7%	-35.9%	-33.8%	-2.0%	-30.7%	3.8%
0.1	-0.8%	-45.4%	-23.2%	-21.2%	-29.2%	-36.4%	-35.7%	-33.8%	-2.0%	-30.7%	3.8%
0.15	-0.8%	-44.6%	-23.2%	-20.4%	-26.6%	-32.4%	-35.1%	-33.7%	-2.0%	-30.7%	3.8%
0.2	-0.8%	-43.4%	-22.8%	-19.4%	-25.8%	-29.6%	-34.3%	-33.3%	-2.0%	-30.7%	3.8%
0.25	-0.6%	-42.2%	-21.4%	-18.8%	-25.0%	-27.7%	-33.4%	-32.8%	-2.0%	-30.7%	3.8%
0.3	1.8%	-41.0%	-18.2%	-17.6%	-23.8%	-23.3%	-32.6%	-32.1%	-2.0%	-30.7%	3.8%
0.35	4.1%	-39.8%	-14.6%	-16.1%	-22.2%	-17.9%	-31.7%	-30.6%	-0.7%	-29.4%	3.9%
0.4	6.5%	-38.6%	-11.1%	-14.6%	-20.9%	-13.0%	-30.8%	-25.1%	1.1%	-27.6%	4.4%
0.45	8.8%	-37.4%	-7.5%	-13.1%	-19.5%	-9.3%	-29.1%	-22.4%	2.9%	-24.6%	5.2%
0.5	11.1%	-36.2%	-4.7%	-11.5%	-17.1%	-5.1%	-25.6%	-21.2%	4.7%	-19.6%	6.3%
0.55	12.1%	-35.0%	-3.1%	-10.0%	-13.0%	-0.1%	-21.4%	-20.0%	8.2%	-14.6%	7.5%
0.6	12.4%	-33.8%	-0.4%	-7.8%	-8.1%	1.2%	-15.8%	-17.2%	13.2%	-9.6%	8.9%
0.65	12.7%	-32.5%	2.7%	-4.0%	-4.6%	3.2%	-12.0%	-14.3%	18.3%	-4.5%	10.7%
0.7	13.1%	-27.0%	5.9%	-1.0%	-1.5%	5.0%	-8.6%	-11.3%	23.3%	0.5%	12.4%
0.75	13.4%	-17.8%	9.0%	4.3%	0.8%	7.0%	-6.1%	-7.7%	28.4%	5.5%	14.1%
0.8	13.7%	-9.7%	12.1%	6.4%	3.9%	9.2%	-3.5%	-3.5%	33.4%	10.5%	15.8%
0.85	14.0%	-6.2%	15.2%	8.7%	8.0%	10.3%	-0.9%	0.8%	40.2%	13.7%	17.6%
0.9	14.4%	-2.6%	18.4%	11.1%	12.0%	11.3%	1.7%	5.0%	49.7%	16.4%	19.3%
0.95	14.7%	1.9%	21.9%	23.7%	16.0%	13.4%	6.1%	9.3%	59.8%	21.1%	21.1%
1	15.0%	7.1%	25.6%	32.8%	22.5%	29.2%	17.7%	13.5%	74.9%	26.5%	26.5%

Table 44. Kansas City District Bridge Heatmap

Percentile	Jun	Aug	Sep	Nov	Dec	Jan	Feb	Mar	Apr	May
0	7.2%	-50.4%	2.1%	-15.4%	-31.4%	-11.8%	-16.2%	-11.8%	-22.1%	1.7%
0.05	7.2%	-50.4%	2.1%	-15.4%	-31.4%	-11.8%	-16.2%	-11.8%	-22.1%	1.7%
0.1	7.2%	-50.4%	2.1%	-15.4%	-30.9%	-10.6%	-16.2%	-11.8%	-22.1%	1.7%
0.15	7.2%	-50.4%	2.1%	-15.4%	-29.0%	-9.6%	-15.7%	-11.8%	-21.3%	1.7%
0.2	9.7%	-50.4%	2.1%	-15.4%	-27.0%	-8.4%	-14.0%	-11.3%	-19.9%	1.7%
0.25	15.2%	-49.6%	2.1%	-15.4%	-25.1%	-6.9%	-12.9%	-10.3%	-18.4%	1.7%
0.3	20.8%	-46.4%	2.1%	-15.4%	-23.2%	-6.1%	-12.2%	-8.7%	-16.9%	1.7%
0.35	26.4%	-43.2%	2.1%	-15.4%	-21.3%	-5.6%	-11.5%	-7.2%	-15.4%	1.7%
0.4	32.0%	-39.9%	2.2%	-15.4%	-19.4%	-4.7%	-10.8%	-5.7%	-14.0%	1.7%
0.45	37.6%	-36.7%	2.2%	-15.4%	-17.5%	-3.7%	-10.2%	-4.1%	-12.5%	1.7%
0.5	43.1%	-33.5%	2.2%	-15.4%	-15.6%	-1.9%	-9.7%	-2.6%	-11.0%	1.7%
0.55	48.7%	-30.3%	2.2%	-15.3%	-13.7%	0.6%	-8.8%	-0.2%	-9.6%	1.7%
0.6	54.3%	-27.1%	2.3%	-15.3%	-11.8%	2.1%	-7.5%	2.3%	-8.1%	1.7%
0.65	59.9%	-23.9%	2.3%	-15.3%	-9.9%	3.0%	-6.1%	5.2%	-6.6%	1.7%
0.7	65.5%	-20.7%	2.3%	-15.3%	-8.0%	4.4%	-4.7%	8.3%	-5.1%	2.2%
0.75	71.0%	-17.5%	2.3%	-15.2%	-6.1%	5.5%	-3.4%	10.6%	-3.7%	3.0%
0.8	76.6%	-14.3%	2.4%	-15.2%	-4.2%	6.5%	-2.0%	12.8%	-0.4%	3.8%
0.85	82.2%	-11.1%	2.5%	-15.2%	-1.1%	9.0%	-0.7%	15.1%	6.3%	4.6%
0.9	87.8%	-7.8%	3.2%	-15.2%	2.2%	11.6%	1.7%	17.3%	13.0%	5.5%
0.95	93.4%	-4.6%	3.9%	-11.2%	5.5%	16.2%	4.2%	19.6%	19.7%	7.7%
1	98.9%	-1.4%	4.6%	-2.1%	8.7%	20.5%	6.6%	21.9%	26.4%	10.5%

Table 45. Central District Paving Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-20.5%	-27.6%	-22.0%	-15.1%	-28.5%	-9.7%	-13.6%	-49.6%	1.5%	-7.3%	-12.4%
0.05	-20.5%	-27.6%	-21.3%	-15.1%	-28.5%	-9.7%	-13.6%	-49.5%	1.5%	-7.3%	-12.4%
0.1	-20.5%	-27.6%	-19.8%	-15.1%	-28.2%	-9.5%	-13.3%	-48.0%	1.5%	-7.3%	-12.4%
0.15	-20.5%	-27.5%	-18.4%	-15.1%	-27.7%	-8.2%	-12.7%	-46.4%	1.5%	-7.3%	-12.4%
0.2	-20.5%	-27.4%	-16.7%	-14.8%	-26.8%	-5.5%	-11.8%	-42.4%	1.5%	-7.3%	-12.3%
0.25	-20.5%	-27.2%	-14.9%	-13.1%	-25.9%	-5.2%	-10.8%	-37.2%	1.6%	-7.3%	-11.8%
0.3	-20.5%	-27.1%	-13.4%	-11.4%	-24.9%	-4.9%	-9.9%	-31.1%	1.6%	-7.3%	-11.3%
0.35	-20.5%	-26.9%	-11.0%	-9.2%	-23.7%	-4.7%	-8.9%	-24.5%	1.6%	-7.3%	-10.7%
0.4	-20.5%	-26.8%	-9.0%	-6.7%	-19.5%	-4.4%	-7.1%	-20.7%	1.6%	-7.3%	-10.2%
0.45	-18.3%	-26.6%	-7.5%	-4.3%	-13.6%	-3.9%	-5.2%	-17.9%	1.7%	-7.3%	-9.6%
0.5	-15.6%	-24.5%	-6.5%	-2.7%	-10.7%	-2.1%	-3.5%	-15.0%	1.7%	-7.3%	-8.4%
0.55	-12.9%	-22.2%	-5.4%	-1.6%	-7.5%	-0.6%	-1.7%	-12.1%	1.7%	-4.5%	-7.1%
0.6	-10.2%	-19.9%	-4.3%	-0.3%	-5.9%	0.0%	0.7%	-9.3%	2.3%	-0.4%	-6.0%
0.65	-7.5%	-15.5%	-3.2%	1.8%	-4.8%	0.7%	3.8%	-6.4%	2.8%	3.6%	-4.6%
0.7	-4.8%	-7.0%	-1.5%	3.6%	-3.0%	1.3%	6.3%	-3.5%	3.4%	7.4%	-0.3%
0.75	-2.1%	-2.9%	0.4%	5.4%	0.1%	2.7%	8.9%	-0.7%	4.0%	11.1%	7.7%
0.8	0.6%	-0.2%	2.1%	7.3%	1.8%	4.0%	11.4%	2.2%	4.5%	14.8%	10.1%
0.85	3.3%	2.9%	3.9%	8.2%	3.4%	5.9%	15.4%	5.1%	5.1%	19.2%	12.6%
0.9	6.0%	6.3%	6.3%	10.6%	7.4%	7.7%	20.5%	7.9%	5.6%	24.8%	17.6%
0.95	8.7%	9.6%	11.0%	15.9%	12.1%	14.9%	24.0%	10.8%	6.2%	30.3%	23.5%
1	11.4%	13.0%	20.8%	23.9%	18.5%	24.7%	28.3%	13.7%	6.8%	35.8%	29.3%

Table 46. Central District Bridge Heatmap

Percentile	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	20.4%	-64.4%	-39.2%	-29.0%	-30.5%	-38.1%	-28.5%	-5.4%	-34.6%
0.05	20.4%	-64.4%	-37.8%	-28.9%	-30.5%	-38.1%	-28.5%	-5.4%	-34.6%
0.1	20.4%	-64.4%	-37.7%	-28.7%	-30.5%	-38.1%	-28.5%	-5.4%	-34.3%
0.15	20.4%	-64.4%	-37.6%	-28.5%	-30.4%	-38.1%	-28.5%	-5.4%	-33.2%
0.2	20.4%	-64.4%	-37.5%	-28.3%	-30.2%	-38.1%	-28.5%	-5.4%	-32.2%
0.25	20.4%	-64.4%	-37.2%	-28.1%	-30.0%	-38.1%	-28.5%	-5.4%	-30.3%
0.3	20.4%	-64.4%	-36.5%	-27.8%	-29.0%	-37.5%	-28.5%	-5.3%	-28.7%
0.35	20.4%	-64.4%	-35.3%	-26.8%	-28.0%	-35.2%	-28.5%	-5.2%	-27.0%
0.4	21.4%	-64.4%	-34.1%	-25.8%	-26.5%	-32.9%	-27.8%	-5.2%	-24.4%
0.45	23.2%	-64.4%	-32.9%	-24.3%	-22.7%	-30.5%	-26.6%	-5.1%	-21.9%
0.5	25.1%	-64.4%	-31.8%	-22.7%	-19.4%	-27.9%	-25.3%	-5.1%	-19.3%
0.55	26.9%	-64.4%	-29.6%	-20.6%	-15.8%	-24.7%	-24.0%	-4.2%	-16.7%
0.6	28.8%	-64.4%	-27.0%	-17.0%	-11.6%	-21.5%	-22.7%	-2.3%	-13.5%
0.65	30.6%	-64.4%	-24.6%	-14.4%	-6.4%	-16.6%	-21.4%	-0.4%	-8.3%
0.7	32.6%	-64.4%	-22.3%	-12.1%	-1.8%	-10.8%	-20.1%	1.5%	-2.7%
0.75	34.9%	-57.7%	-18.0%	-9.7%	2.2%	-5.0%	-18.8%	3.5%	2.8%
0.8	37.3%	-46.0%	-12.5%	-5.3%	6.1%	0.5%	-17.5%	4.8%	8.4%
0.85	39.7%	-34.4%	-6.8%	-0.9%	10.2%	6.3%	-16.2%	5.8%	13.9%
0.9	42.0%	-22.8%	-1.1%	3.6%	14.8%	11.6%	-14.9%	7.3%	19.5%
0.95	44.4%	-11.2%	6.8%	8.0%	19.1%	17.3%	-13.6%	9.2%	25.3%
1	46.7%	0.5%	17.0%	40.6%	23.4%	23.0%	-12.2%	11.1%	33.0%

Table 47. St. Louis District Paving Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-25.0%	-49.3%	-13.3%	-8.0%	-25.4%	-29.1%	-28.7%	-18.2%	-41.4%	-14.6%	-28.9%
0.05	-25.0%	-49.3%	-13.2%	-6.2%	-25.4%	-29.1%	-28.3%	-18.2%	-41.4%	-13.8%	-28.7%
0.1	-25.0%	-49.3%	-12.7%	-1.0%	-25.4%	-28.6%	-27.3%	-18.2%	-41.4%	-12.7%	-21.2%
0.15	-25.0%	-49.3%	-12.3%	-0.7%	-25.1%	-27.9%	-26.2%	-18.2%	-38.8%	-11.5%	-16.2%
0.2	-25.0%	-49.3%	-11.8%	-0.5%	-24.8%	-27.1%	-25.1%	-17.7%	-33.3%	-10.4%	-14.3%
0.25	-25.0%	-49.3%	-11.3%	-0.4%	-24.4%	-24.6%	-23.3%	-17.0%	-26.2%	-9.5%	-12.4%
0.3	-25.0%	-49.3%	-10.8%	-0.3%	-23.0%	-22.0%	-18.6%	-16.3%	-21.6%	-8.5%	-11.6%
0.35	-25.0%	-49.3%	-10.4%	-0.1%	-21.3%	-19.5%	-17.0%	-15.6%	-17.1%	-7.5%	-10.9%
0.4	-24.5%	-49.3%	-9.9%	0.0%	-20.1%	-18.4%	-14.8%	-15.1%	-12.5%	-6.6%	-10.1%
0.45	-22.4%	-49.3%	-8.7%	0.3%	-19.1%	-17.3%	-12.6%	-14.2%	-10.9%	-5.6%	-9.4%
0.5	-20.3%	-49.3%	-7.0%	1.5%	-17.3%	-16.2%	-10.4%	-13.1%	-8.4%	-4.6%	-8.3%
0.55	-18.2%	-49.3%	-5.4%	2.9%	-14.7%	-15.1%	-8.0%	-12.0%	-3.9%	-3.7%	-5.9%
0.6	-16.0%	-49.3%	-3.7%	4.2%	-12.0%	-13.9%	-4.5%	-10.4%	1.4%	-2.7%	-3.2%
0.65	-13.9%	-49.3%	-2.1%	5.5%	-9.4%	-12.8%	-2.1%	-8.4%	6.8%	-0.9%	0.0%
0.7	-11.8%	-46.4%	-0.4%	6.9%	-6.2%	-11.7%	1.3%	-5.5%	9.3%	-0.6%	1.7%
0.75	-9.8%	-41.4%	1.3%	8.4%	-2.5%	-10.4%	6.1%	-1.0%	12.0%	-0.4%	3.1%
0.8	-8.6%	-36.4%	2.9%	10.0%	2.3%	-8.3%	11.2%	4.0%	14.7%	-0.3%	6.4%
0.85	-7.3%	-31.4%	4.6%	11.6%	7.3%	-6.1%	16.5%	8.8%	17.4%	-0.1%	9.4%
0.9	-5.9%	-26.4%	6.3%	13.2%	12.3%	-3.9%	20.5%	12.0%	25.7%	0.0%	13.2%
0.95	-4.5%	-21.4%	7.9%	15.0%	17.3%	-1.5%	24.3%	25.7%	33.8%	11.4%	20.3%
1	-3.2%	-16.4%	33.4%	17.0%	22.3%	15.7%	29.9%	30.6%	41.8%	33.6%	29.8%

Table 48. St. Louis District Bridge Heatmap

Percentile	Sep	Oct	Nov	Dec	Jan	Feb	Mar	May
0	-6.5%	-21.7%	26.6%	2.8%	-9.5%	0.9%	-12.7%	-26.4%
0.05	-6.5%	-21.7%	26.6%	2.8%	-9.5%	1.3%	-12.7%	-26.2%
0.1	-6.5%	-21.6%	27.2%	2.8%	-9.5%	3.7%	-12.7%	-24.0%
0.15	-6.5%	-21.5%	27.9%	2.8%	-9.3%	6.0%	-12.6%	-23.0%
0.2	-6.5%	-21.4%	28.6%	2.8%	-9.0%	8.3%	-12.6%	-20.7%
0.25	-6.5%	-20.5%	29.2%	2.8%	-8.8%	10.6%	-12.6%	-17.4%
0.3	-5.1%	-17.7%	29.9%	2.8%	-8.5%	13.0%	-11.7%	-13.9%
0.35	4.4%	-14.7%	30.6%	2.8%	-7.8%	15.3%	-10.2%	-7.4%
0.4	9.7%	-11.7%	31.3%	2.8%	-7.1%	17.9%	-8.7%	1.0%
0.45	10.2%	-10.3%	32.0%	2.8%	-6.3%	21.0%	-7.3%	2.2%
0.5	10.8%	-9.0%	32.7%	2.8%	-5.6%	24.2%	-5.8%	3.4%
0.55	11.4%	-7.8%	33.4%	2.9%	-3.1%	27.3%	-4.3%	4.6%
0.6	11.9%	-6.4%	34.1%	2.9%	-0.7%	30.5%	-2.8%	5.9%
0.65	12.5%	-5.0%	34.8%	2.9%	1.7%	33.6%	-1.2%	7.1%
0.7	13.1%	-3.8%	35.4%	3.1%	4.2%	36.7%	0.2%	8.3%
0.75	13.6%	-2.5%	36.1%	3.4%	6.7%	39.4%	2.3%	9.5%
0.8	14.2%	-0.6%	36.8%	3.7%	11.1%	42.1%	4.7%	10.7%
0.85	14.8%	2.1%	37.5%	4.0%	15.6%	44.8%	6.8%	11.9%
0.9	15.3%	8.6%	38.2%	4.3%	20.1%	47.5%	11.1%	13.5%
0.95	15.9%	12.2%	38.9%	4.7%	24.6%	50.2%	15.8%	18.2%
1	16.5%	17.5%	39.6%	5.0%	29.1%	52.9%	20.6%	45.4%

Table 49. Southwest District Paving Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	35.2%	-14.1%	-25.7%	-25.8%	-27.0%	-2.7%	-29.2%	-25.1%	-12.8%	-17.7%	-19.2%
0.05	35.2%	-9.4%	-25.3%	-25.1%	-26.9%	-2.2%	-28.5%	-25.1%	-12.8%	-17.7%	-19.2%
0.1	35.2%	-7.5%	-23.7%	-23.6%	-24.3%	-1.0%	-25.1%	-25.1%	-12.8%	-15.8%	-19.2%
0.15	35.2%	-6.1%	-22.0%	-22.1%	-23.6%	0.1%	-23.2%	-23.3%	-12.8%	-13.1%	-17.0%
0.2	35.2%	-5.7%	-19.9%	-20.6%	-21.3%	1.3%	-21.5%	-21.4%	-12.8%	-9.1%	-13.8%
0.25	35.2%	-5.3%	-17.6%	-18.2%	-16.5%	2.5%	-19.9%	-19.5%	-12.8%	-3.4%	-11.6%
0.3	35.2%	-4.9%	-15.6%	-17.9%	-15.5%	3.7%	-18.5%	-18.1%	-12.5%	-1.2%	-10.3%
0.35	35.2%	-3.4%	-14.1%	-17.2%	-14.7%	4.9%	-17.3%	-17.8%	-10.0%	0.1%	-9.6%
0.4	35.2%	-1.5%	-12.9%	-16.5%	-13.6%	6.1%	-15.8%	-17.5%	-7.4%	1.6%	-8.8%
0.45	35.2%	0.9%	-12.0%	-16.2%	-12.7%	7.2%	-14.3%	-17.2%	-4.8%	3.2%	-8.1%
0.5	35.2%	3.1%	-9.0%	-15.9%	-11.7%	8.4%	-12.8%	-16.9%	-2.3%	4.7%	-6.8%
0.55	35.2%	4.2%	-6.9%	-15.6%	-10.8%	9.6%	-11.3%	-16.6%	-0.4%	6.2%	-4.5%
0.6	35.2%	5.0%	-5.8%	-14.9%	-9.5%	11.3%	-9.9%	-16.3%	1.2%	7.8%	-2.6%
0.65	36.4%	5.7%	-4.6%	-13.5%	-8.4%	13.0%	-8.4%	-16.0%	3.3%	9.3%	-0.9%
0.7	43.9%	6.6%	-3.3%	-11.3%	-7.1%	14.8%	-6.9%	-15.1%	5.2%	10.9%	0.8%
0.75	51.4%	7.4%	-2.0%	-9.2%	-6.0%	16.5%	-5.4%	-13.3%	6.9%	12.6%	2.9%
0.8	58.8%	8.1%	-1.6%	-6.5%	-4.2%	18.3%	-3.9%	-11.5%	8.2%	15.5%	7.5%
0.85	66.3%	9.7%	-0.1%	-3.8%	-1.3%	20.0%	-2.4%	-9.7%	9.6%	18.4%	12.6%
0.9	73.8%	11.9%	3.0%	0.1%	4.6%	21.8%	-1.0%	-6.6%	11.0%	21.0%	17.5%
0.95	81.2%	15.3%	6.2%	5.4%	8.5%	23.5%	0.5%	-1.9%	12.4%	23.3%	22.0%
1	88.7%	25.8%	22.7%	14.3%	17.6%	25.3%	2.0%	4.9%	43.7%	25.7%	32.3%

Table 50. Southwest District Bridge Heatmap

Percentile	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-20.3%	-33.3%	-31.5%	-11.5%	-12.1%	-36.9%	-8.9%	-25.5%
0.05	-20.3%	-33.3%	-31.4%	-11.5%	-12.1%	-36.9%	-8.9%	-23.0%
0.1	-20.3%	-33.3%	-30.9%	-11.4%	-12.1%	-36.9%	-8.4%	-20.5%
0.15	-20.3%	-33.3%	-30.4%	-11.2%	-12.1%	-36.9%	-6.9%	-15.9%
0.2	-20.3%	-33.0%	-29.9%	-10.3%	-11.6%	-36.9%	-5.7%	-10.9%
0.25	-20.2%	-30.8%	-29.4%	-8.5%	-10.2%	-36.0%	-4.5%	-7.6%
0.3	-20.1%	-28.6%	-28.9%	-8.2%	-8.9%	-32.1%	-3.0%	-4.7%
0.35	-20.1%	-26.4%	-28.4%	-8.0%	-7.6%	-27.3%	-1.2%	-1.9%
0.4	-20.0%	-24.2%	-27.9%	-7.8%	-6.2%	-22.5%	0.8%	1.0%
0.45	-19.9%	-22.0%	-27.4%	-7.5%	-4.8%	-17.7%	2.7%	4.9%
0.5	-19.9%	-19.8%	-26.9%	-7.1%	-3.5%	-15.4%	4.7%	8.7%
0.55	-19.8%	-17.6%	-26.0%	-5.0%	-2.1%	-12.8%	6.6%	10.3%
0.6	-19.7%	-15.5%	-24.9%	-2.0%	-0.7%	-10.2%	8.6%	12.3%
0.65	-19.7%	-13.3%	-23.7%	2.1%	1.0%	-5.5%	10.6%	14.2%
0.7	-18.4%	-11.1%	-22.6%	6.3%	3.6%	-0.5%	13.1%	16.1%
0.75	-14.5%	-8.9%	-21.5%	11.2%	6.3%	3.6%	16.1%	18.8%
0.8	-10.7%	-6.7%	-17.8%	16.9%	9.1%	5.8%	19.7%	21.6%
0.85	-6.8%	-4.5%	-12.2%	22.5%	12.0%	9.9%	24.1%	24.5%
0.9	-3.0%	-2.4%	-6.6%	28.1%	14.9%	14.1%	27.3%	27.0%
0.95	0.9%	-0.2%	-1.1%	35.2%	18.6%	18.2%	30.1%	30.0%
1	4.7%	2.0%	4.5%	42.2%	22.6%	22.4%	32.9%	38.1%

Table 51. Southeast District Paving Heatmap

Percentile	Jun	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
0	7.6%	-14.6%	-8.1%	-19.9%	-26.8%	-9.9%	-16.1%	-3.4%	-26.6%	-7.6%	-30.0%
0.05	7.6%	-14.6%	-8.1%	-19.3%	-26.6%	-9.9%	-16.1%	-3.3%	-26.6%	-7.6%	-29.4%
0.1	7.6%	-14.6%	-8.1%	-18.0%	-24.8%	-9.9%	-14.7%	-2.3%	-26.4%	-7.6%	-28.5%
0.15	7.6%	-14.6%	-7.8%	-16.3%	-23.1%	-9.9%	-13.6%	-0.7%	-25.7%	-7.6%	-27.5%
0.2	7.6%	-14.6%	-7.3%	-14.1%	-22.2%	-9.6%	-13.2%	0.4%	-24.5%	-7.6%	-25.9%
0.25	8.4%	-14.6%	-6.7%	-12.7%	-21.4%	-8.2%	-12.9%	1.3%	-23.4%	-7.6%	-23.6%
0.3	11.7%	-14.6%	-6.4%	-11.2%	-20.4%	-6.4%	-12.5%	2.3%	-22.2%	-7.4%	-21.5%
0.35	11.8%	-14.6%	-6.1%	-9.3%	-19.9%	-4.7%	-12.1%	3.4%	-21.3%	-6.8%	-20.1%
0.4	11.8%	-14.6%	-5.9%	-6.9%	-19.6%	-4.0%	-10.2%	4.9%	-20.4%	-6.1%	-17.7%
0.45	11.9%	-14.6%	-5.6%	-3.7%	-19.3%	-3.1%	-8.6%	6.6%	-19.6%	-5.2%	-15.1%
0.5	11.9%	-14.6%	-5.5%	-1.7%	-18.6%	-2.0%	-6.5%	7.6%	-18.6%	-4.3%	-12.6%
0.55	12.0%	-14.6%	-5.3%	0.0%	-17.7%	-0.6%	-4.7%	8.3%	-16.4%	-3.4%	-10.4%
0.6	12.3%	-14.6%	-4.9%	1.7%	-16.4%	0.2%	-3.5%	8.9%	-14.6%	-2.3%	-6.7%
0.65	14.0%	-14.6%	-4.6%	6.2%	-14.9%	1.2%	-0.2%	9.8%	-12.7%	-0.3%	-2.7%
0.7	15.8%	-14.6%	-4.1%	7.1%	-13.4%	3.2%	4.0%	10.9%	-9.8%	1.7%	0.7%
0.75	18.2%	-14.6%	-3.0%	7.8%	-12.1%	5.3%	8.0%	12.1%	-6.8%	4.0%	3.5%
0.8	20.5%	-11.2%	-1.9%	8.5%	-10.2%	8.6%	11.4%	13.2%	-4.1%	6.6%	5.5%
0.85	22.9%	2.3%	-0.6%	10.8%	-6.1%	13.6%	15.5%	14.9%	-1.7%	9.3%	7.1%
0.9	25.2%	15.8%	0.7%	16.3%	-1.1%	18.8%	21.3%	17.3%	1.9%	11.9%	9.1%
0.95	27.6%	29.2%	3.8%	22.7%	6.8%	26.2%	28.3%	20.1%	3.7%	14.4%	12.4%
1	29.9%	42.7%	17.7%	34.3%	15.5%	36.0%	42.3%	24.0%	9.0%	16.9%	19.3%

Table 52. Southeast District Bridge Heatmap

Percentile	Nov	Dec	Jan	Feb	Mar	Apr	May
0	-26.3%	-15.0%	-36.7%	19.9%	-13.3%	-16.0%	-17.8%
0.05	-26.3%	-15.0%	-36.7%	19.9%	-13.3%	-16.0%	-17.3%
0.1	-20.1%	-15.0%	-36.6%	19.9%	-13.3%	-16.0%	-14.7%
0.15	-11.3%	-15.0%	-35.2%	19.9%	-13.3%	-16.0%	-10.9%
0.2	-9.0%	-15.0%	-33.1%	23.9%	-13.3%	-15.1%	-8.2%
0.25	-8.7%	-15.0%	-30.6%	28.7%	-12.6%	-14.2%	-7.0%
0.3	-8.4%	-15.0%	-26.9%	32.4%	-9.8%	-13.3%	-5.7%
0.35	-8.1%	-13.6%	-23.3%	33.7%	-8.9%	-12.5%	-4.6%
0.4	-7.8%	-12.3%	-21.3%	35.0%	-8.5%	-11.6%	-3.8%
0.45	-7.5%	-10.9%	-19.7%	36.2%	-7.8%	-10.7%	-3.0%
0.5	-7.1%	-9.6%	-18.1%	37.4%	-7.0%	-6.7%	-2.2%
0.55	-6.8%	-8.3%	-14.6%	37.6%	-6.0%	-2.4%	-1.4%
0.6	-6.5%	-6.9%	-12.0%	37.9%	-4.7%	3.0%	-0.6%
0.65	-6.2%	-5.6%	-10.1%	38.7%	-3.4%	8.4%	0.2%
0.7	-5.9%	17.1%	-8.1%	39.5%	-0.3%	11.4%	2.0%
0.75	-5.6%	43.4%	-5.9%	40.8%	3.6%	14.4%	5.2%
0.8	-5.3%	69.7%	-2.1%	42.5%	8.3%	17.5%	8.5%
0.85	-5.0%	73.8%	2.3%	47.6%	13.1%	20.5%	10.4%
0.9	-4.7%	77.2%	6.8%	52.2%	18.0%	23.5%	11.5%
0.95	-4.4%	80.6%	10.9%	55.9%	22.8%	26.6%	12.6%
1	-4.1%	84.1%	15.8%	59.7%	27.6%	29.6%	14.3%

Appendix B: Mock Tool User Interface

This appendix includes screenshots of a mocked-up tool that could be used as a blueprint for a future lightweight optimization application. Figure 36 through Figure 43 show user interface tabs to complete the following steps:

- Upload the latest project information, projects available for letting now, versus what has already been let.
- Set monthly targets, with research defaults available.
- Set soft constraints by project type.
- Set soft district constraints.
- Visualize optimization results.
- Visualize Monte Carlo post optimization simulation variance.
- Visualize project slippage outcomes.
- Visualize Monte Carlo post optimization probabilistic contractor bidding results.

Figure 36. User Interface - Data Upload

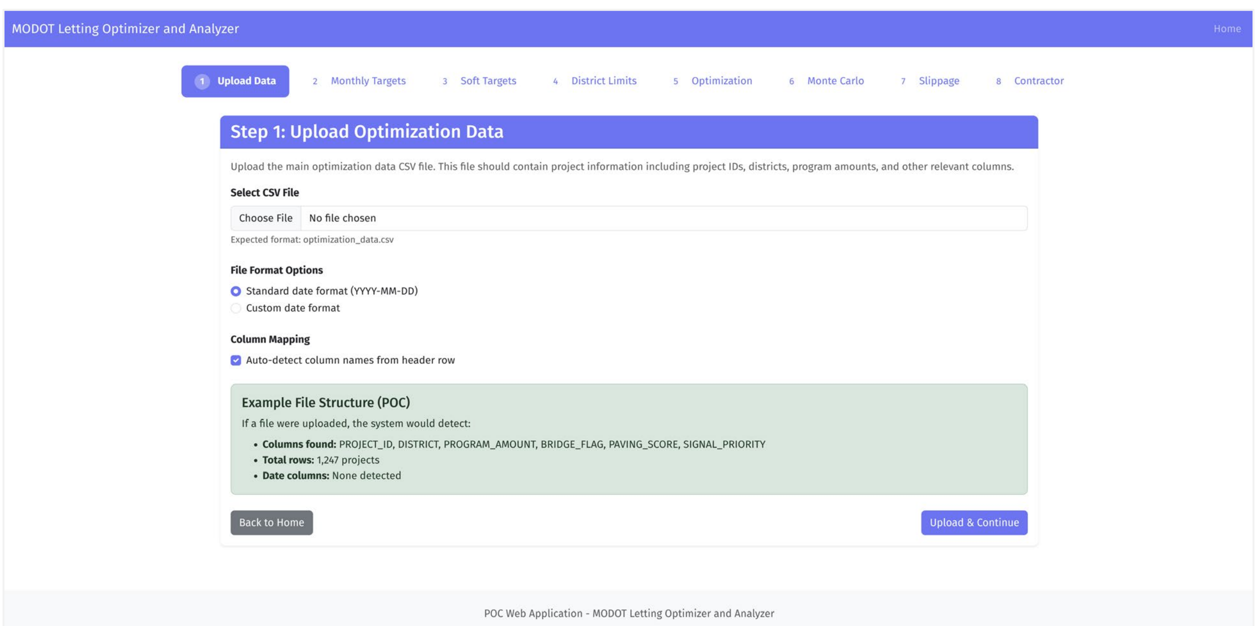

Figure 37. User Interface - Set Monthly Targets

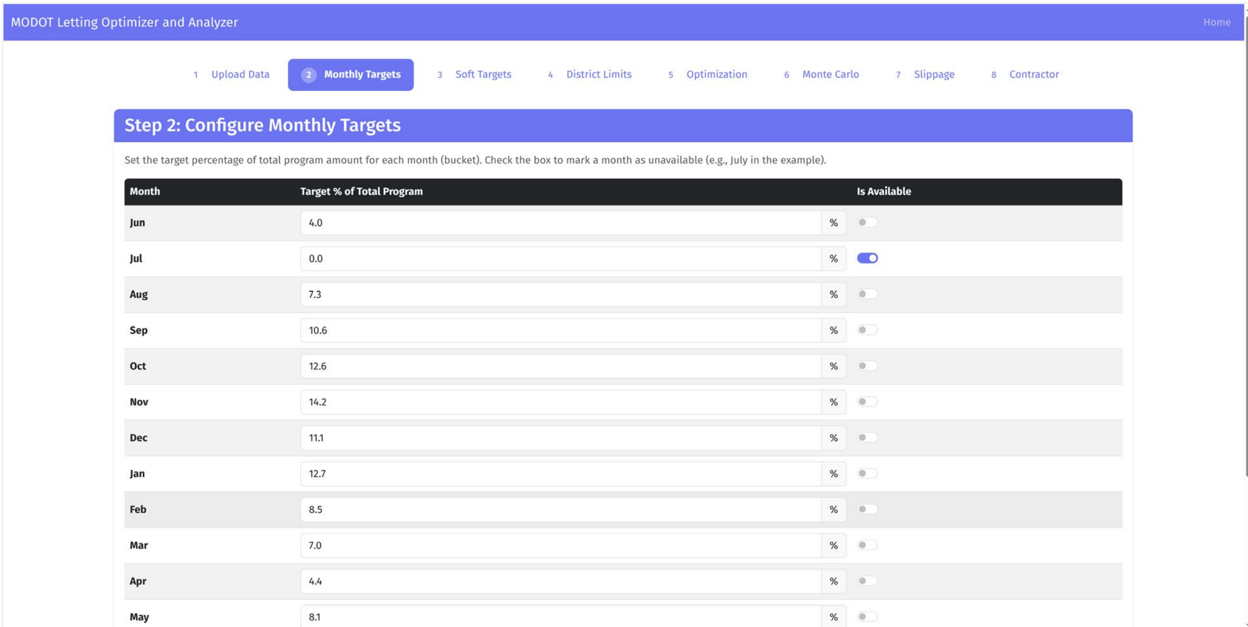

Figure 38. User Interface - Set Project Type Constraints.

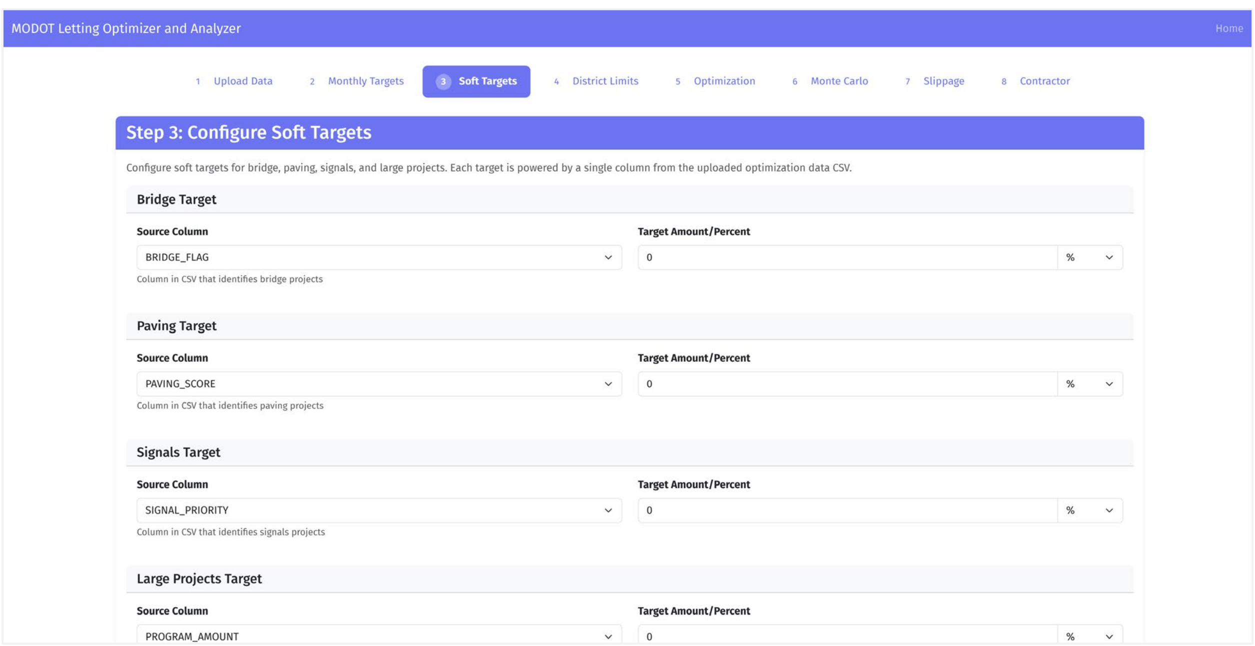

Figure 39. User Interface - Set District Constraints

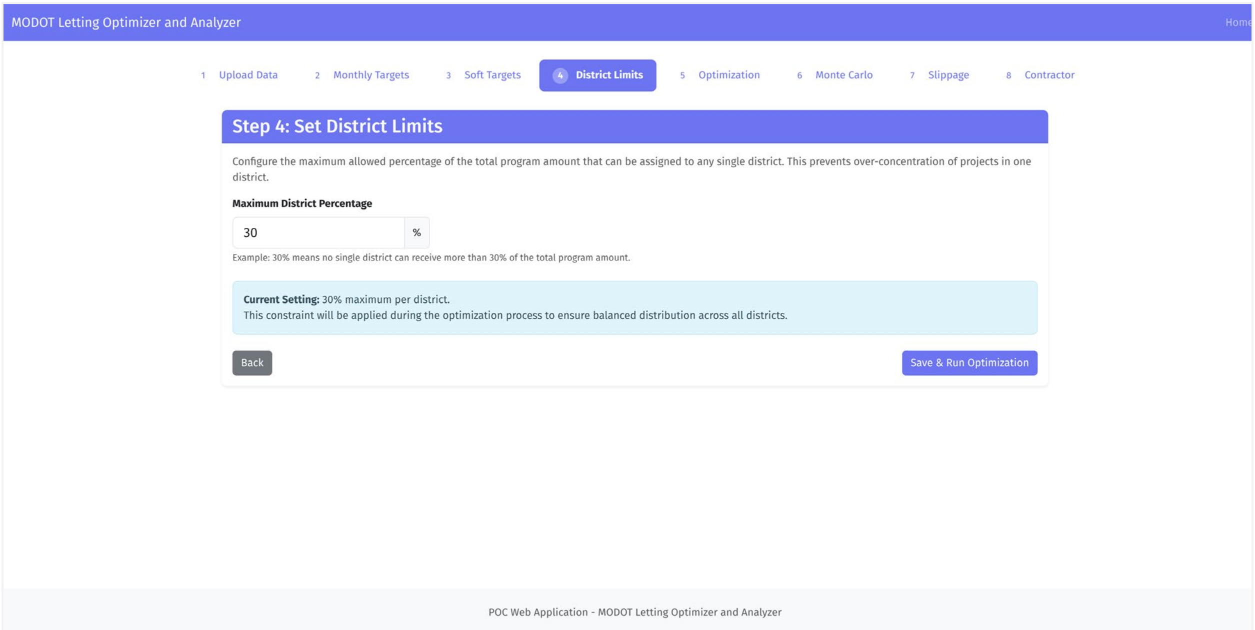

Figure 40. User Interface - Review Optimization Results

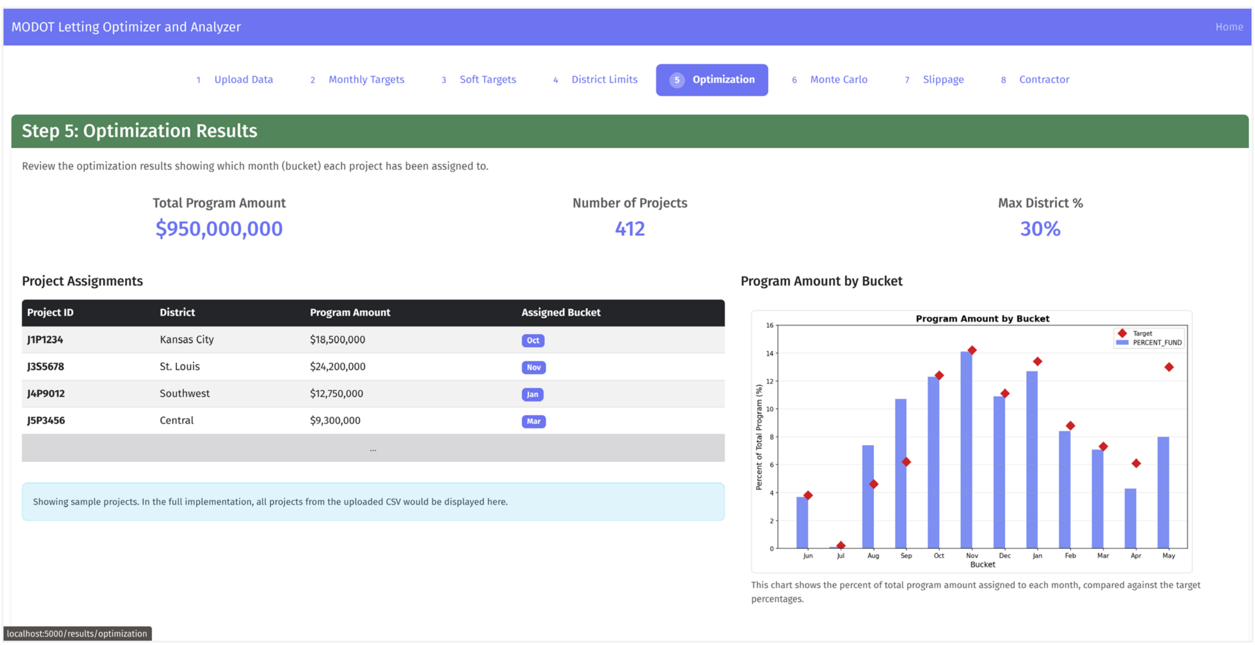

Figure 41. User Interface - Review Monte Carlo Simulation Results

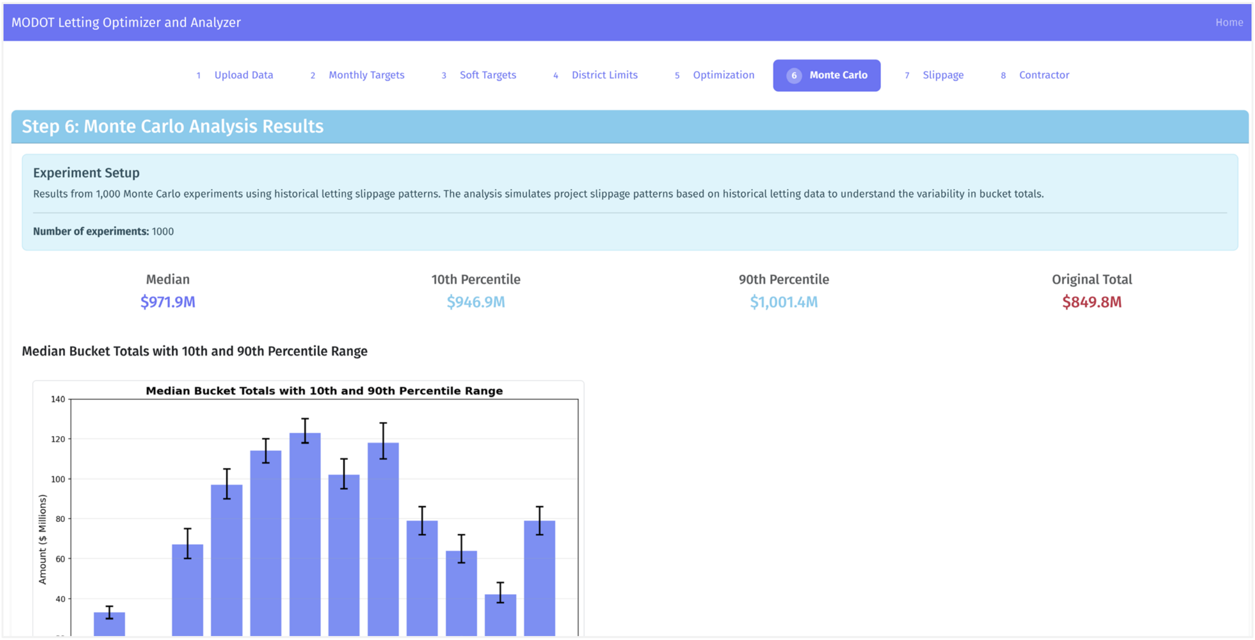

Figure 42. User Interface - Visualize Monte Carlo Slippage Results

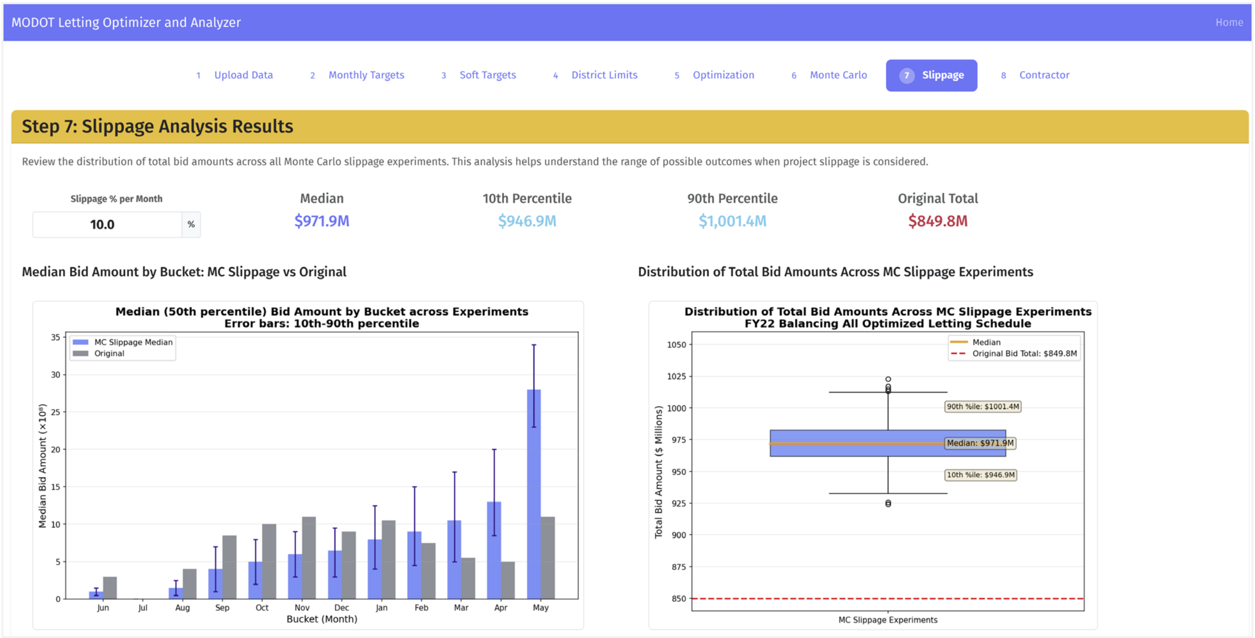

Figure 43. User Interface - Visualize Contractor Bidding Simulation Results