Space-Time Modeling:
Indego Bike Share Demand in Philadelphia

Jack Bader

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1 Data Selection

For our analysis, we opted to use Indego bike share data from Q2 in 2025. This quarter is a natural extension of our prior work using data from Q1 2025. Applying the same framework to consecutive time periods allows for more directly comparable results of spatial and time patterns, model performance, and error analysis.

Additionally, Q2 captures considerably different seasonal dynamics than Q1. While Q1 tracked a transition from Winter to Spring, Q2 captures a vastly different transition from Spring to Summer. Demand in Indego bikes is likely to increase over a transition to warmer weather and longer daylight. Conversely, colleges end their Spring Semester usually in early May in the middle of Q2, likely causing a decrease in demand. These are just a couple examples of the temporal factors that can affect changes in Indego bikeshare demand.

2 Exploratory Data Analysis

Before delving into our modeling results, we conducted exploratory data analysis to gain a better understanding of the temporal and spatial patterns in bikeshare demand.

2.1 Temporal Demand Patterns

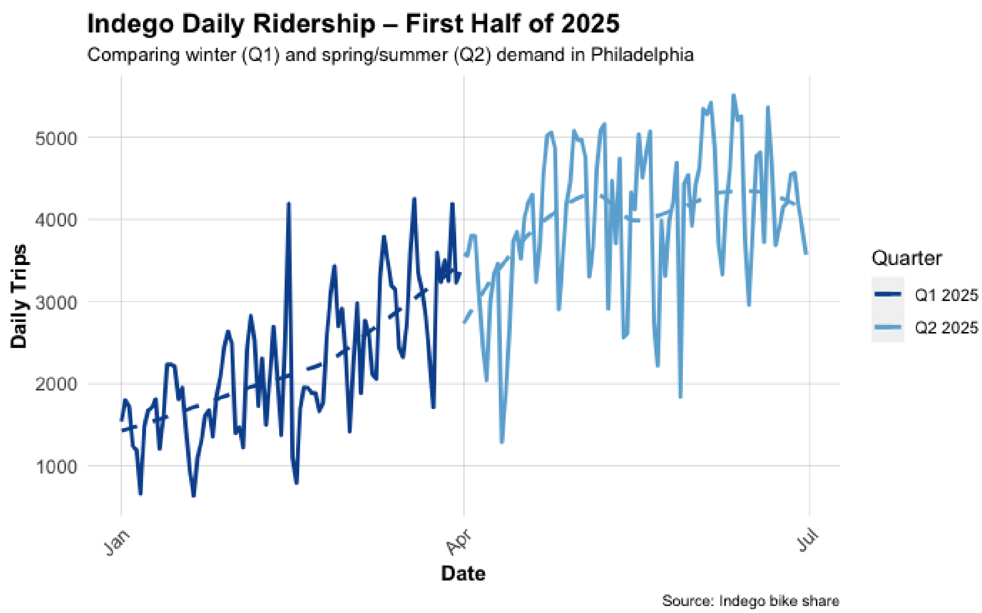

Figure 1: Indego Daily Ridership

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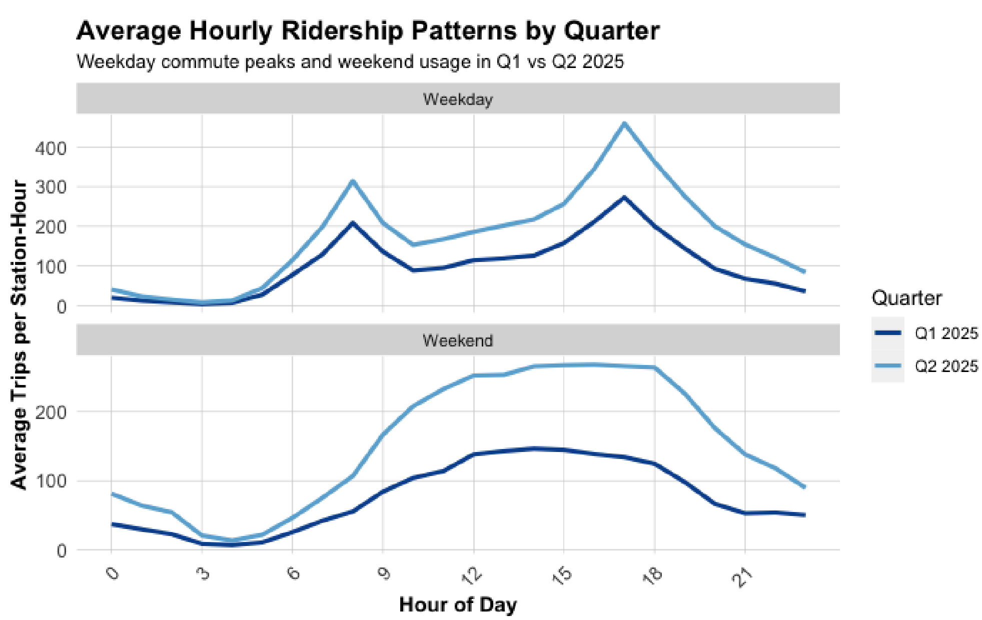

Figure 2: Average Hourly Ridership by Weekday/Weekend

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From figure 1, we observe the number of daily Indego trips increase from Q1 to Q2 in 2025, likely due to warmer, more biker-friendly weather. The trend (slope) of daily ridership remains fairly constant from January to May then begins to flatten out, which is the Summer break effect. Overall variability seems consistent as well, with some outliers such as the Superbowl in February.

In figure 2, the shape of the average hourly ridership look near-identical across quarters for both weekdays and weekends, with more trips at every timestep for Q2. On weekdays, the peak times are at rush hour at 9 am and 5 pm respectively. There is a massive increase in weekend usage during the daytime from sunrise to sunset.

2.2 Spatial Demand Patterns

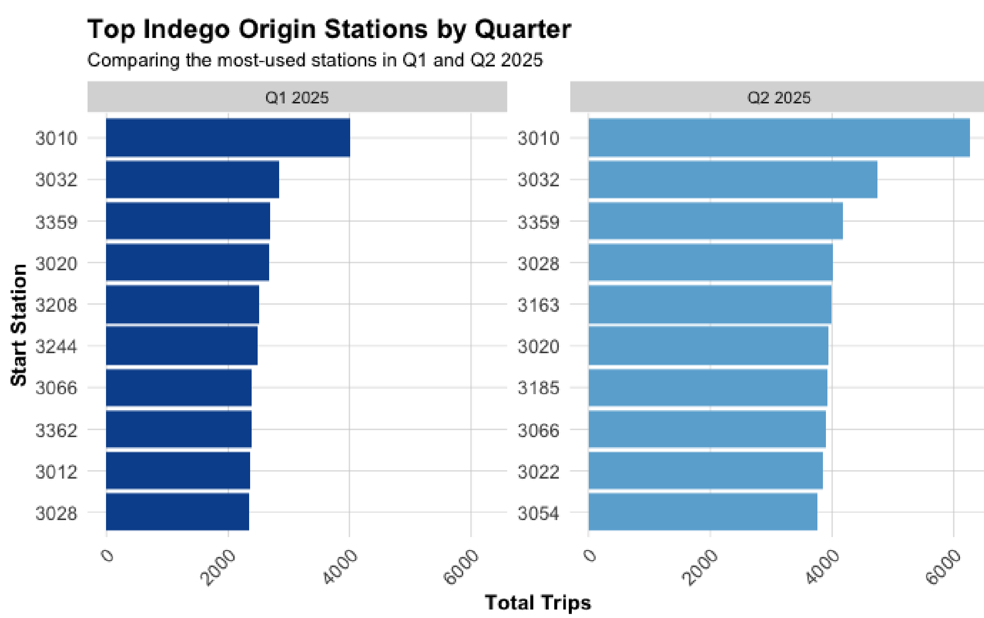

Figure 3: Top Indego Origin Stations

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In figure 3, we see that a majority of the top 10 Indego origin stations shared across both quarters. This suggests some stations are always in higher demands regardless of the time of year.

2.3 Temperature Patterns

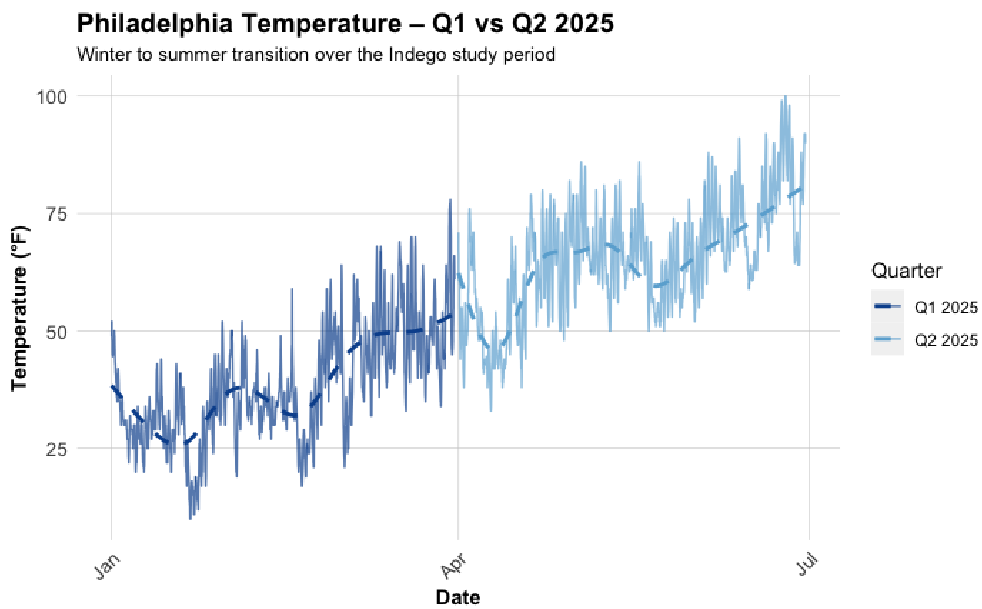

Figure 4: Temperature in Philadelphia

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From figure 4, we see temperature increase linearly from January to July with constant variability across quarters. This pattern is expected and confirms our suspicions that a warmer temperature correlates to increased Indego bike activity.

3 Modeling Approach and Comparison Results

3.1 Model Specifications

Below are our five original linear regression models that we used to predict bike share demand.

- **Model 1: Time + Weather:** time-of-day + day-of-week + temperature + precipitation.
- **Model 2: + Temporal Lags:** Model 1 + lags (1 hour, 3 hours, 24 hours).
- **Model 3: + Demographic:** Model 2 + median income + % public transit + % white
- **Model 4: + Station Fixed Effects:** Model 3 + FE
- **Model 5: + Rush Hour Interaction:** Model 4 + rush hour

3.2 Model Comparison (MAE)

Table 1: Model comparison in Q2: Mean Absolute Error (test set).

Model	**MAE (trips)**
Model 1: Time + Weather	0.81
Model 2: + Temporal Lags	**0.62**
Model 3: + Demographic	0.86
Model 4: + Station FE	0.86
Model 5: + Rush Hour Interaction	0.85

Model 2 outperformed all other models by a wide margin with the lowest MAE score. In a previous study, we also found that this same model performed the best for data in 2025 Q1 as well.

We can interpret this finding as evidence that adding temporal lags substantially increases model accuracy because bike share demand is highly persistent over short time periods. A station is generally busy over a few hour window or at the same time each day, demonstrating cyclical behavior.

The higher model complexity of models 3-5 harm model performance on the test set. The addition of these variables harm predictive power as they do not capture any meaningful patterns in bike share demand. It is also possible that these models overfit to the training data, leading to worse performance on unseen data.

4 Space–Time Error Analysis

4.1 Temporal Error Patterns

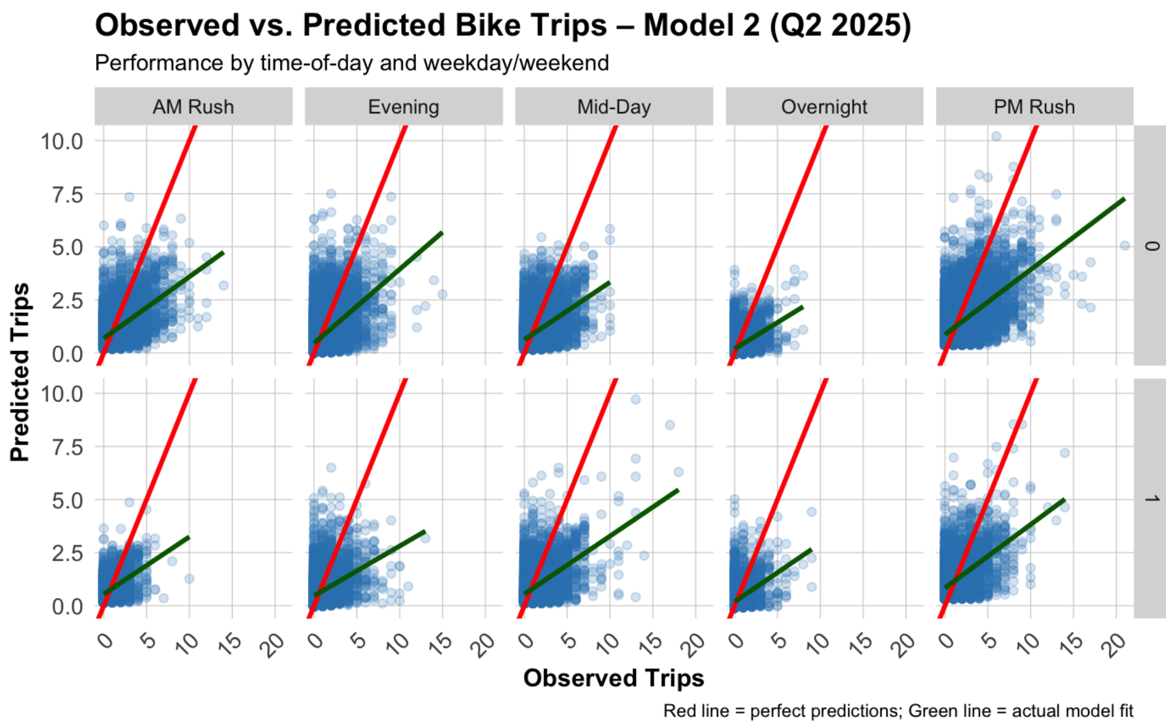

Figure 5: Observed vs. predicted bike trips for Model 2 by time-of-day and day type.

In figure 5, we visualize the predicted (model) number of trips on the Y-axis and observed (true) on the X-axis, separated by weekday (0) vs. weekend (1) and time of day. The red line represents perfect predictions whereas the green line shows the model fit. In all 10 cases, as the number of observed trips increases, the green line falls more and more below the red line, signifying the model under predicting.

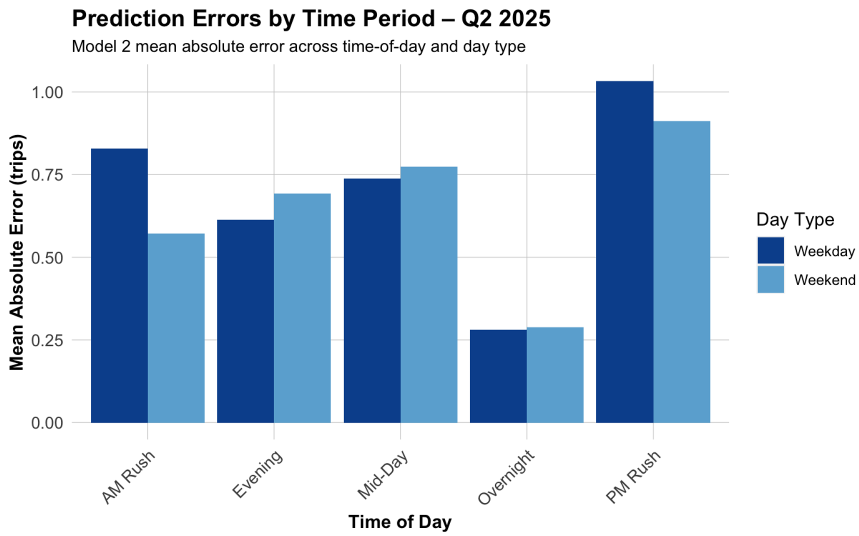

Figure 6: MAE by time-of-day and day type

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In figure 6, MAE prediction errors are smallest for both weekdays and weekends during overnight when demand is low with very few trips. For weekdays, MAE is larger during rush periods than non-rush. This makes sense since this is when the most people are taking trips, which has the most variation due to other variables such as weather, temperature, etc. The opposite is true for weekends since peak rush hours don't occur on these days.

4.2 Spatial Error Patterns

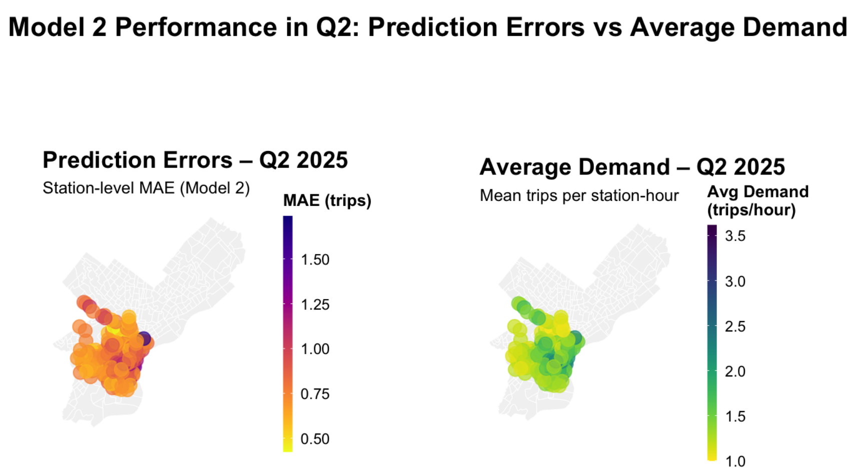

Figure 7: Station-level MAE.

Figure 7 connects the dots of the presence of a relationship between bikeshare demand and predicton errors: errors are larger when demand is higher. These two plots show exactly that. Evidently, Center City has the most demand for bikes as its central location with the most offices, restaurants, museums alike. As a result, these stations become the hardest to predict because of noisier variance from things such as bad weather. Conversely, stations outside of Center City have lower errors and demand with less short term volatility.

4.3 Demographic Error Patterns

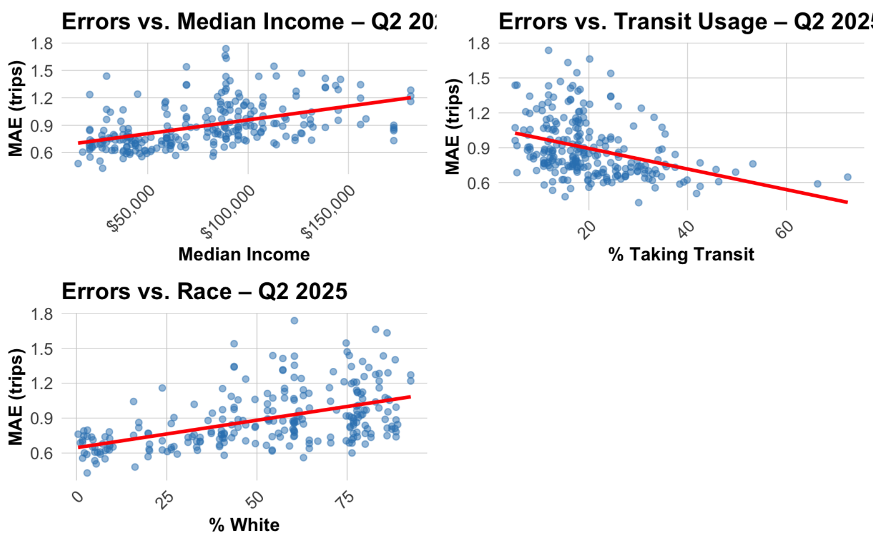

Figure 8: Prediction Errors (MAE) vs. Demographic Data.

Figure 8 suggests there are no strong, linear relationships between MAE and select demographic data. It appears that errors rise slightly when higher median income or % white. The intuition is that the central neighborhoods with more stations (and demand) are often higher-income and predominantly white, leading to larger errors. Prediction errors decrease with higher levels of % transit. This contradicts the argument that higher demand causes larger errors. Since these variables don't appear to be strongly correlated with our errors, adding them into our model 3 severely hurt performance.

5 Improving Model 2: Feature Engineering and Poisson Regression

5.1 Feature Engineering Rationale

To continue our modeling workflow, we selected **Model 2** as our best model. In this section our goal is to engineer additional features to improve upon this model even further to try and achieve a lower MAE. Let's recall from our error analysis that we found that under prediction occurred most in high demand times such as Weekday PM Rush and areas such as Center City. To remedy this systematic under prediction, we should engineer variables that are likely to capture these effects that are not currently being explained well by our model.

Below is a list of newly featured variables to add to **Model 2**:

- **Nice weather indicator**: 1 if temperature is between 60–75°F and precipitation = 0; 0 otherwise. We used this to capture high demand when weather conditions are optimal. We found earlier that warm weather had a substantial impact on increasing demand for bikes.
- **Same hour last week (lag1week)**: lag of trips at the same station and hour, 7 days earlier. Lag variables have already been seen to add a considerable amount of predictive power to our model. This additional lag makes intuitive sense since the same time each week for each station should observe the relative same level of demand. Our idea is that this variable should help us mitigate underprediction during the busiest time periods.
- **Distance to Center City**: distance in km from each station to City Hall. Since Center City seems to be the most in-demand for bikes and have the highest prediction errors, this was the most logical choice for increased spatial modeling. Our goal is that the model will upweight stations closer to Center City to help further limit large underpredictions in this region.

5.2 Poisson Regression

Since our target variable of trips per hour / station is made up of non-negative integers, a natural alternative to an OLS linear regression is a count regression method such as the Poisson. Also, note that we tested for overdispersion, which we found none, so the Poisson count regression is more suitable than the Negative Binomial. The Poisson regression could offer better predictions by treating the relationship between mean-variance differently and better capturing the regressors as multiplicative effects.

5.3 Effect on Model Performance

Table 2: Effect of new features on Model 2 in Q2 2025.

Model	**MAE (trips)**
Model 2 (Linear, baseline)	0.625
Model 2 (Linear, new features)	0.625
Model 2 (Poisson, baseline)	0.691
Model 2 (Poisson, new features)	0.651

For Q2, adding the new features to **Model 2** did not have any affect on MAE of 0.625, suggesting that these variables do not offer any predictive power beyond what was already captured by our other predictors (time-of-day, day-of-week, lags, etc.). It is likely that this model does improve upon high-demand errors to some degree but were cancelled out by performing worse elsewhere. In this case, adding model complexity with these selected variables offers no improvement.

Also, the Poisson regression performs worse overall. This suggests that the mean-variance relationship is not representative of the data and imposes too many constraints on our model, leading to higher MAE scores.

5.4 Error Analysis for Model 2 (Linear, new features)

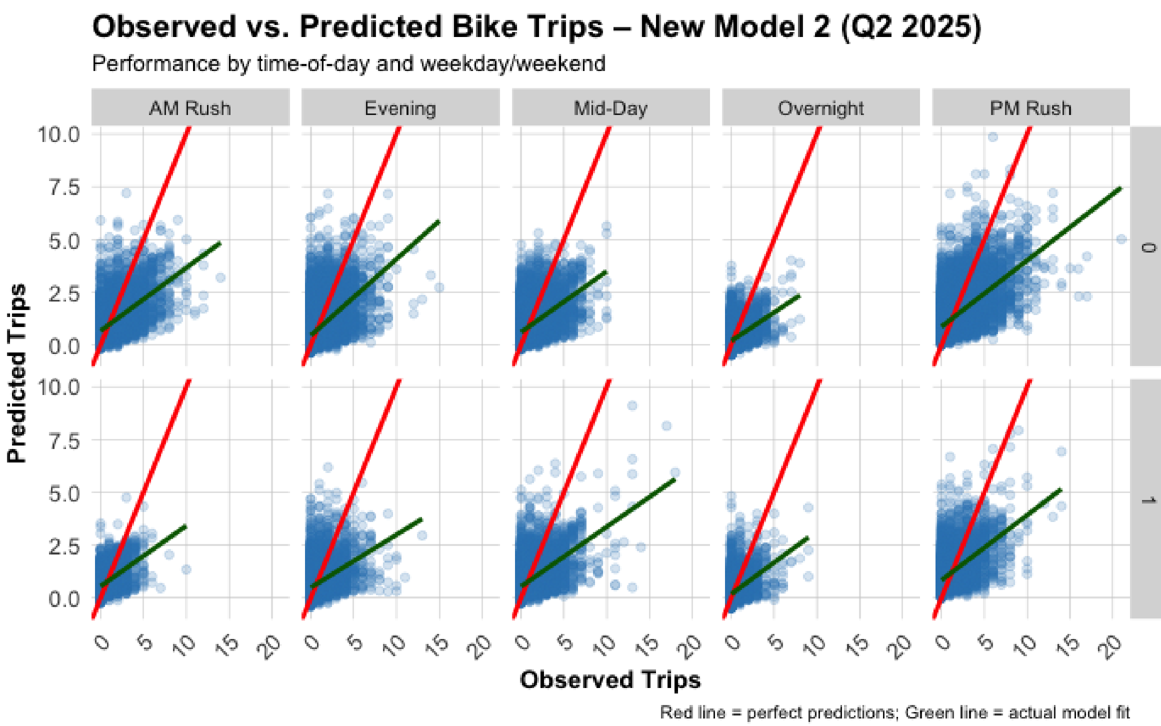

Figure 9: Observed vs. predicted bike trips for Model 2 by time-of-day and day type (New Model).

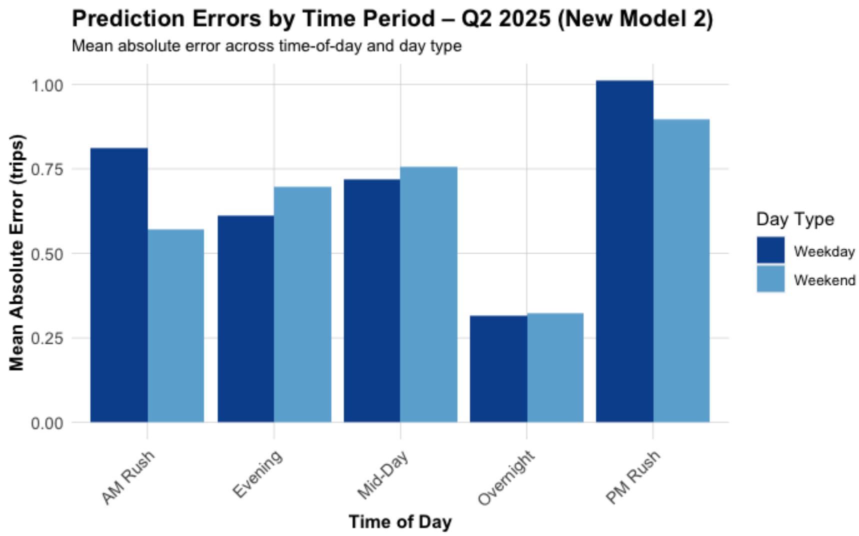

Figure 10: MAE by time-of-day and day type (New Model).

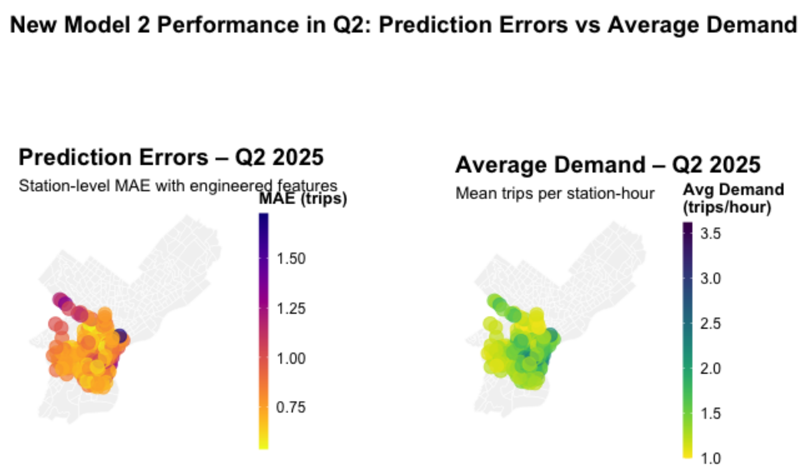

Figure 11: Station-level MAE (New Model).

From the new error-analysis plots above, we see virtually no difference from our original model 2. This supports our claim that the added features did not improve the model and were unable to better capture the high-demand areas, times, and weather conditions.

6 Critical Reflection on Deployment

Our best linear **Model 2** achieves an MAE of **0.625** for trips per station/hour in Philadelphia for 2025 Q2. On average, our model forecasts within one trip of the true count, This performance is reasonably good to use some operational planning decisions such as setting rebalancing targets. However, rebalancing would be systematically under predicted the most for stations experiencing high demand regions and times. Therefore, this model could be used to set a lower bound of bike distributions throughout these stations as support tool, but humans in the loop should validate its decisions and monitor the flow of demand and supply based on external considerations.

From an equity perspective, there are not strong causes for concern of disparities for certain neighborhood demographics. Center City is the most under predicted region where there is a higher % of white individuals and higher levels of income. It is unreasonable to classify this group as underserved since the reality is that they are the ones who benefit the most from Indego bikes already. The bigger issue is that the spread of the Indego station network does not reach neighborhoods outside of Central Philadelphia. This greatly hinders access to them for lower income communities as they are not able to utilize Indego bike services nearby their homes. One option is to increase the Indego network by building stations that will reach these communities, increasing their access to use the bike-share program. Then, to prevent future algorithmic disparities, Indego should set minimum standards for each neighborhood and monitor model decision-making for potential biases targeting underserved groups.

Our model does miss patterns of significant days such as holidays, sporting events, and school calendar. It also misses some other spatial features such as distance to nearest park and points of interest (restaurants, offices, bars) to name a few. An assumption likely to not hold during deployment is independent errors across space and time. It is likely that things like a signficant day or a massive storm would cause correlation between errors that propogate across the whole Indego network and can span multiple hours. Another violated assumption is that all relationships of the target variable to each regressor are linear and additive. For example, it is likely that the amount of rain (precipitation) can largely vary in impact. Light rain would not deter many from taking a bike over the bus or subway; however, pouring rain would force almost everyone to avoid taking a bike. If given more time, we would likely seek out more data to better capture nuances in bike-share demand. Persistent under prediction is likely a sign that there are not enough variables explaining bike-share demand. We would continue to explore different predictors in our model building workflow to form a better, more accurate model to capture extreme peaks in time-space and weather.