Good crystal balls are hard to buy and costly to maintain. For this reason, public policy is often based on assumptions and guesses. Even by the standards of the average policy, bicycle data has tended to be difficult to procure and, often, fairly anecdotal.

The chart above includes actual bicycle counts from the Hawthorne Bridge and the statistic reported by the Portland Bureau of Transportation (PBoT) for the past twenty years. The data appears to indicate that the growth of bicycling at this important location has leveled off.
Luckily, Portland – and particularly Portland State – has a better data than elsewhere. Today, we have a number of interesting surveys – Metro, the Portland City Auditor, the Downtown Business Census, and the American Community Survey to work with. Most importantly, since August 8, 2012, we have had hourly bicycle counts from our most important bike path – the Hawthorne Bridge – to work with.

Last year I took part in the work of the City Club Bicycle Policy Committee. All of the members of the committee worked hard and we produced an excellent report. I took the lead in the statistics supporting the report. Much of the data from that effort forms the basis of the work reported here. As more data has become available I have updated and extended the earlier research. It goes without saying that this paper does not represent a position of the Portland City Club or the members of the committee.

Bicycling shares much in common with other emerging activities. Early days are slow, then there is a period of acceleration, and finally a period of saturation. This is true in analyzing sales of television sets, epidemiology, and even to visits to Indian owned casinos.

The standard mathematical model is called the logistic curve. Many analysts use the term “S-Curve” because of its standard “S” shape.

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When the City Club committee started work on bicycle policy last year, I remarked on the resemblance of Hawthorne Bridge data on rides per year to the standard logistic curve.

To find the total number of commuters from the Downtown Business Census & Survey, I multiplied the proportion of employees reporting bicycles as their commuting option. The Hawthorne Bridge data is taken from the Portland Bicycle Count Report 2012 and divided by two since the Hawthorne Bridge data reports rides not riders. These two dissimilar sources share a similar pattern, both sets of data on central city bicycling start slow, accelerate, and then appear to have leveled off in the past few years.

The two series are highly correlated – $R^2 = .7791$ – and are prepared by different authors with different perspectives. The coincidence of shape adds credibility to both series.

The standard formula for a logistic curve is:

$$Y = \frac{L}{1 + a \exp(-x \cdot t)}.$$
The usual approach is to transform the equation into a form where a standard linear regression can be used to calculate the intercept and slope. The results from the linear regression can be transformed back into the original a and b parameters.

One disadvantage of the logistic curve analysis is that the value “L” is often assumed. In this case, I assumed 10,000 commuters as a departure point. The logistic curve for employees reporting bicycles as their commuting mode is consistent with theory:

The results for Hawthorne Bridge rides isn’t as classic by any means:
The more evocative bicycle commuters’ logistic curve is significant at the 5% level. The more aggressively climbing Hawthorne Bridge rides curve is significant at the 1% level.\(^5\)

Obviously, a time series analysis with only twelve observations is highly preliminary.

Our intuition would lead us to believe that something clearer is happening. As Jonathon Moss said of the recent City of Portland Auditor’s survey:

> The Office of the City Auditor released its 23rd annual Community Survey today and the results reveal yet another sign that the amount of people riding bicycles in Portland has reached a stubborn plateau.\(^6\)

Luckily, we have a much better dataset to work with. On August 8, 2012, the City of Portland received its first automated bicycle counter. The counter’s results are posted to the internet at [http://portland-hawthorne-bridge.visio-tools.com/](http://portland-hawthorne-bridge.visio-tools.com/).

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\(^5\) “Significance” simply represents the chance that these results would be due to pure chance. This is an often abused measure since analysts often have tried enough different specifications that pure chance delivers and apparently significant result. In this case, only one model and one level of \(L\) were used.

Starting in October 2012, we began following the data in a systematic fashion. From the beginning, it was obvious that bicycling is both seasonal and responsive to weather conditions. Since there was no a priori reason to believe that bicyclists’ response to temperature, precipitation, or wind is linear, I used both the average temperature and the square of temperature in order to capture the curvature of response. The same variables were used for wind and precipitation. Craig Beebe, a City Club committee member, recommended adding sunset as well, since many riders prefer riding during daylight hours.

Development of the statistical model was stopped at that point since testing a thousand variations would have invalidated the statistical results. The model has been unchanged since February 2012 – only updated ridership and meteorological data has been added. At an early date a “dummy” variable was added to address weekends and holidays when ridership falls dramatically.7

The model can be split in two – one for workdays and one for holidays and weekends – but this reduces the degrees of freedom for weekends and holidays significantly. When this was tried, there was little change in the results, so the dummy variable approach for handling low ridership periods was kept.

The results from a standard multiple regression are:

<table>
<thead>
<tr>
<th>SUMMARY OUTPUT</th>
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<tbody>
<tr>
<td>Regression Statistics</td>
</tr>
<tr>
<td>Multiple R</td>
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<tr>
<td>R Square</td>
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<tr>
<td>Adjusted R Square</td>
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<tr>
<td>Standard Error</td>
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<tr>
<td>Observations</td>
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<tr>
<td>df</td>
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<tr>
<td>Regression</td>
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<tr>
<td>Residual</td>
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<tr>
<td>Total</td>
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</table>

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
<th>Lower 99.0%</th>
<th>Upper 99.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-4485.912351</td>
<td>981.2884652</td>
<td>6.2E-06</td>
<td>-7023.95928</td>
<td>-1947.865174</td>
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<td></td>
</tr>
<tr>
<td>tMean</td>
<td>241.6707571</td>
<td>34.01531478</td>
<td>7.104763211</td>
<td>174.8279858</td>
<td>308.5135284</td>
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<td></td>
</tr>
<tr>
<td>tMean*2</td>
<td>-1.547911846</td>
<td>0.296146393</td>
<td>-5.226684687</td>
<td>-2.12986282</td>
<td>-0.965960871</td>
<td></td>
<td></td>
</tr>
<tr>
<td>prcp</td>
<td>-10.67386753</td>
<td>32.36677682</td>
<td>0.329778513</td>
<td>0.74172</td>
<td>0.590139918</td>
<td></td>
<td></td>
</tr>
<tr>
<td>prcp*2</td>
<td>104.9790662</td>
<td>41.42179937</td>
<td>2.534391742</td>
<td>2.534391742</td>
<td>2.534391742</td>
<td></td>
<td></td>
</tr>
<tr>
<td>windAvg</td>
<td>10.67386753</td>
<td>32.36677682</td>
<td>0.329778513</td>
<td>0.74172</td>
<td>0.590139918</td>
<td></td>
<td></td>
</tr>
<tr>
<td>windAvg*2</td>
<td>-1.953650582</td>
<td>2.38174859</td>
<td>-0.82027056</td>
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<tr>
<td>Holiday</td>
<td>-2815.48711846</td>
<td>0.296146393</td>
<td>-5.226684687</td>
<td>-2.12986282</td>
<td>-0.965960871</td>
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<td></td>
</tr>
<tr>
<td>Sunset</td>
<td>104.9790662</td>
<td>41.42179937</td>
<td>2.534391742</td>
<td>2.534391742</td>
<td>2.534391742</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Order</td>
<td>-0.03402478</td>
<td>0.317628343</td>
<td>-0.10712136</td>
<td>-0.10712136</td>
<td>-0.10712136</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

7 In this case a one represents Saturday, Sunday, or a holiday. A zero represents a standard workday.
The model works very well. Overall, the three meteorological variables and sunset, explain 82% of the variation in rides across the Hawthorne Bridge. Meant temperature, mean precipitation, the dummy variable for weekend/holidays, and time of sunset are significant at the 99% level. Wind is not significant.

Most interestingly, the variable named “Order” is not significant. Order represents the number of days since the Hawthorne Bridge data became first available. If the number of rides was increasing over the 454 days we have in the data set, the coefficient would be greater than zero and the result would be significant. In the ponderous terms of a statistician, we cannot reject the hypothesis that the coefficient is zero. Put more simply, there is no evidence from the daily Hawthorne Bridge data over the past sixteen months that rides on the bridge are increasing – even after weather effects are factored in.

Charting the actual data against the predictions shows that meteorology isn’t the only variable we could have used. The most obvious failing of the model is that it predicts that riders will decide to bicycle the Hawthorne Bridge rather than enjoy the Christmas holidays with their families. This is reflected by the predictions of additional rides (blue lines) over the Christmas holidays. The model also fails to account for the annual nude ride (the red peak in June.)

The model can also be used to complete a forecast of 2013 results. Although we do not have weather yet for the rest of December, we have no a priori reason to believe that the weather in the near future will differ wildly from our historical experience in past December months.
We also used the model to complete the daily record from 2012 – daily counts were missing from July 11, 2012 through August 9, 2012.8

Overall, our preliminary results for 2013 appear to continue the horizontal portion of the logistic curve. The hefty growth forecasted for December 2013 reflects the model's over forecast for Christmas.

Reverse engineering the values reported in Portland Bureau of Transportation’s Bicycle Counts is more difficult. As noted above, the reported number is described as an average of summer midweek rides in 2010 and as “peak use” in 2012. Peak use in 2013 was undoubtedly higher than in previous years at 9,834 on Saturday, June 8th. The average of summer midweek rides in 2012 was higher than 2013.

The problem is that neither methodology matches the reported value:

<table>
<thead>
<tr>
<th>Year</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>8,136&lt;sup&gt;9&lt;/sup&gt;</td>
</tr>
<tr>
<td>2012</td>
<td>8,305&lt;sup&gt;10&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

8 PBoT reported a previous data set of daily rides on the Hawthorne Bridge in the Portland Bicycle Count 2012 that predates the Hawthorne bicycle counter. This data was used to complete 2012.
10 September 25, 2012.
2012 Midweek Summer Average: 7,109

Overall, the most logical interpretation – the simple average of rides on Tuesday, Wednesday, and Thursday in the months of June through September yields a fall in 2013 versus 2012 – a reduction from 7,109 to 6,790.

Is this the end of bicycling? No. It may establish that the rapid growth phase has developed into the slower growth of a mature product or technology.

Both Roger Geller of the Portland Bureau of Transportation and our recent City Club report have addressed this issue. Once enthusiasm isn’t the primary fuel, careful planning is required. Both the Geller study and the City Club report emphasize the use of bicycle boulevards over less secure routes.

Our methodologies have little overlap. Roger Geller analyzed the current policy goals and then derived the steps necessary to reach the objective.

Our approach was both simpler and more data oriented. We reproduced the excellent study by Mauricio Leclerc. He conducted a multiple regression by census tract, looking for the relationship between different types of infrastructure and geography on bicycle commuting. Mr. Leclerc concludes:

Variable “bike lane feet per square mile” is significant in all years (at the 90 percent confidence level, 95 percent confidence level in 2000). The signs are as expected. The models for 2000 and 1990 suggest that an additional 1,000 feet of bikeways is associated with roughly a 0.035 to 0.037 percent increase in bicycle mode share, other things being equal. The 1996 and “all periods” model suggest that the same increase in bikeways is associated with a 0.060 percent in the percentage of bicycle commutes.

This spring we repeated the study, with additional detail on the types of bikeways. Our a priori hypothesis is that we would find stripes on the pavement and other various risky forms of infrastructure would fail to attract bicyclists. We also felt that safer options would prove more correlated with increased bicycling than other forms of infrastructure.

12 Ibid. Pages 10-11, Appendix B.
The regression indicates that Bike Boulevards and Low Traffic Through Streets are highly correlated with ridership. Shoulders – either wide or shallow – show little relationship to ridership.

Removing the remaining eight infrastructure variables from the regression yields:
The regression strongly represents vindication of our a priori hypotheses – distance and slopes discouraging bicycling while good – safe – infrastructure enhances it.

As data becomes available we can move from correlation to causality. If we could generate bike path data on the same schedule as the Portland Auditor and American Community surveys, we should eventually be able to use a granger causality test. At the moment, this is years away from becoming a possibility.

In conclusion, the preliminary data indicates that we are approaching the flatter region of the logistic curve. If there is a desire to expand bicycle commuting, a sustained effort needs to be mounted to establish safer paths.