Combining Hedonic with Multilateral Indexes for Turnover and Chain Drift in Transactions Data Consumer Price Indexes

Gregory Kurtzon

March 2025

Abstract

This paper combines hedonics and rolling window multilateral indexes in transactions data to fix the problems of product turnover and chain drift. Data such as transactions data hold the potential to eliminate substitution bias in elementary price indexes with quantities concurrent with prices, but using these quantities can cause chain drift (non-circularity). The typical solution in national consumer price indexes (CPIs) is to use multilateral indexes, but these don't fully eliminate chain drift. The large amount of product entry and exit is usually delt with by making unit value prices, but this causes biases from quality changes and Jensen's inequality. Previous research has studied different multilateral formulas, window lengths, and rolling window splicing methods, and noted that sales and product turnover are highly connected to chain drift. Therefore, hedonic imputation should help all these issues at the same time. I create Pakes (2003) style hedonic indexes using IRI grocery and drug store data from 2001-2011 with dummy variables for all variable values plus interactions and bootstrap the indexes to check for overfitting. I make Caves, Christensen, and Diewert (1982) (CCDI) indexes over rolling window lengths that span the entire range of data and make Multiperiod Identity Tests and Laspeyres-Paasche spreads to evaluate them. Chain drift typically falls for rolling windows up to 7 months, but doesn't disappear, and can actually get better or worse for longer windows until the window length converges to all twelve years. The hedonic indexes have an acceptable level of variance and don't gain from having interaction variables. But only imputing values for observed prices unambiguously helps chain drift by smoothing the effects of sales, while a full imputation for all entering and exiting goods can have a reverse drift pattern, which can be better or worse.

1 Introduction

Transactions data is now being widely demanded and used in official national CPIs in many major nations. The promise of these new data sources is the ability to avoid possible sampling biases from obtaining the whole universe of transactions, and also to use concurrent quantities and prices to make monthly chained indexes and avoid substitution bias. However, there are two major problems with using this data. One is that there's a large number of new and entering goods, and with the whole universe already in the sample, there is no room to use the typical methodology of substituting another good for an exiting one. Another problem is that using the raw concurrent quantities gives the index chain drift, here defined as non-circularity, meaning that even if all prices return to their original levels, the chained index level will not return to 1 as it should. This paper studies the use of hedonics to deal with both good turnover and non-circularity, and its combination with multilateral indexes that are typically used to treat non-circularity.

The method typically used to incorporate new and exiting goods by those countries that use a large amount of transactions data is to make a unit value index over each thin band of goods' characteristics. However, unit value indexes will treat all quality improvements in new goods as price increases, and will also suffer from Jensen's inequality, $E\left(\frac{p_{it}}{p_{i,t-1}}\right) \leq \frac{E(p_{it})}{E(p_{i,t-1})}$, so they would suffer some degree of upwards bias. Unit value indexes are also not justified by economics and often have erratic behavior. Making a pure hedonic index, as per Pakes (2003) however, would solve these problems and be economically justified.

Chain drift is typically caused by price bouncing. Price index formulas are approximations for an arbitrary expenditure function, derived under the conditions that quantities are consumed in the period they are purchased. In fact, they are all discrete time approximations the same continuous Divisia index which is a the Cost-of-Living index for any consumer preferences.[1] All these approximations will work well close the point of expansion which is when the prices between any two periods in a chain link are equal, and if consumers do not stockpile goods. If the prices converge as the interval grows shorter, these approximations are very similar, as shown in Kurtzon (2022). However, if prices bounce up and down between periods, and if consumers stockpile goods, chain drift can occur. For example, during a sale the price falls a large amount for one period, and the quantity is very high as consumers stock up. After the sale, the price returns but the quantity may be lower than before since consumers are consuming some stored goods. A Törnqvist index will have a lower mean share for the upward price movement than the lower one, and the index will drift downward despite the prices returning, and so the index will be non-circular. Other patterns in quantities can also occur, as described in Hill (2006a), which have different biases in indexes.

However, how to measure chain drift isn't clear. If we had an index

[1] See Balk (2005), Diewert (1976), Divisia (1926), Reinsdorf (1998), CPI Manual ILO 2004.

without chain drift to measure a proposed index against, a true measure as a gold standard, we wouldn't need another index and there would have been no problem in the first place. But of course there is not measure that we can be sure isn't biased. Sometimes, such as noted in Ivanic, Diewert, and Fox (2011) (IDF), one can look at an index and see that a 20% deflation rate for some goods in a weekly aggregated index, is 'unreasonable', using priors on how prices behave. This 'reasonability' test is very vague and informal, but can be a kind of last resort for extreme indexes.

Or, using the definition of chain drift, the Multiperiod Identity Test (MPID test), invented by Walsh (1901) (referred to as the MPID test in Diewert (1993)), measures the degree of noncircularity by the difference between an index with all prices returning to their first value, and 1. To make an index with all prices returning to the first value, an additional period is added to a chained index, with the base of the last period and the current period being the first. Let $P(\tau, t)$ denote a price index from periods τ to t. Then the MPID test is

$$P(1,2)\,P(2,3)\,P(3,4)\cdots P(T-1,T)\,P(T,1) \tag{1}$$

, with a difference from 1 denoting noncircularity.

But a problem is that the last chain link in the MPID test, $P(T,1)$, will span a much longer period of time than the typical link $P(t-1,t)$, and the prices from period 1 to T will be more dissimilar, meaning the index will be a worse approximation of the expenditure function and of true consumer preferences. Hill (2006b) for example, shows that if long time spans for index links are combined with short time spans, even superlative indexes, which are second order approximations to arbitrary preferences[2], will diverge from each other, showing that they become worse approximations. Another problem is that over longer periods of time there is more turnover in goods - there are fewer goods sold in both 1 and T than between other links t-1 to t, which also makes the $P(T,1)$ less reliable.

While there have been many other papers on chain drift and multilateral indexes (including but of course not limited to Diewert and Fox (2022), Fox, Levell, and O'Connell (2023), Feenstra and Shapiro (2003), Melser and Webster (2021)), and on hedonic price indexes, there has been little on the combination of them. The time dummy characteristics hedonic index (or time dummy hedonics index) is a multilateral method that is also a hedonic index that uses good's characteristics, but it has the limitation that the characteristics coefficients are held constant over the whole multilateral window. Since the main bias of excluding new and entering goods, as described in Pakes (2003) and Erickson and Pakes (2011), is that characteristics coefficients change, this can lose much of the bias reduction of a hedonic index. Since a hedonic index can be thought of as simply redefining goods as characteristics, this is similar to holding prices constant. Diewert and Shimizu (2024) study this and limit the bias from holding characteristics prices constant by using only two adjacent periods at a time, which is a very short rolling window subject to more chain

[2] See Diewert (1976).

drift, and compare it to an expanding window which uses all available data but holds characteristics prices constant longer. DeHaan & Krisinich (2014) also study monthly full imputation hedonic indexes in a rolling window Caves, Christensen, and Diewert (1982) (CCDI) (or Törnqvist GEKS) multilateral index. However, the main contributions of my paper are (1) the bootstrapping of full imputation hedonic indexes with dummy variables, to show variance and strength of the specification; (2) showing the combination of full imputation indexes and a multilateral of all window lengths for a long period of time, and how it converges to circularity with a MPID test; (3) the chain drift reducing effects of hedonic indexes; (4) the behavior of Laspeyres-Paasche multilateral indexes and the pattern of index formulas converging to each other.

The rest of the paper is as follows. Section 2 describes the hedonic regression and bootstrapping method. Section 3 describes the problem of chain drift and the CCDI multilateral index, the Multiperiod Identity Test used, and the Laspeyres-Paasche Indexes that attempt to measure the degree of chain drift. Section 4 describes the data and results. Section 5 concludes.

2 Hedonics for Transactions Data

2.1 Method

Hedonic indexes were constructed for each month using the methodology of Pakes (2003), where a separate regression is run for every month. The strength of this method is that there are no restrictions holding the coefficients constant over time, and only information from each period alone is used to make predictions. If characteristics prices change significantly over a month, this method is more accurate. Log prices were regressed on a set of dummy variables, with one dummy variable for every possible value of each of the goods' characteristics. For example, for cold cereal, there is a dummy variable for every store, a dummy for every value of "Type of Grain", including a dummy for "Assorted", "Multi Grain", "Corn", etc., and similarly for the other variable's values.

Chained Törnqvist indexes were made using the predicted prices and monthly quantities. Two types of imputed prices were made: non-missing only and full imputation. The first replaces all observed prices with a predicted price from the hedonic regression, replacing every observed price for item i in period t, p_{it}, with the predicted price $\hat{p}_{it}$. This type of imputation helps study the effects of hedonics without it's effect on entering and exiting goods. The second method imputes all missing prices, so that the predicted prices from each regression were used in place of both actual and missing prices for every good that was ever in the sample. For periods that the store for a given missing good is not in the sample, it simply sets the store dummy coefficient for period t to zero, $\beta_{store,t} = 0$. When a good exits or enters, the share for the month for a good that was not present was therefore zero, and the Törnqvist averages it with the share of the good after it enters or before it exits. Thus, there is a

price relative that includes all entering and exiting goods to avoid the selection problems of quality changes. When a good is not in the index for two consecutive period, the average share is zero, and so it is effectively excluded.

The regression model for prices p_{it} for period t and item, dummy variable D_{ci} which is one if item i has characteristic c and zero otherwise, characteristic coefficient β_{ct}, and error ε_{it} is

$$\ln p_{it} = \Sigma_c D_{ci} \beta_{ct} + \varepsilon_{it} \tag{2}$$

Thus every price in the data was replaced by

$$\hat{p}_{it} = \Pi_c \beta_{ct}^{D_{ci}} \tag{3}$$

and the hedonic Törnqvist index between periods t-1 and t, where the expenditure share of item i in period it is s_{it}, is

$$T_{t-1,t}^{H} = \Pi_i \left(\frac{\hat{p}_{it}}{\hat{p}_{i,t-1}} \right)^{\frac{s_{i,t-1}+s_{it}}{2}} \tag{4}$$

and the index level is

$$I_t^H = \Pi_{\tau=1}^{t} T_{\tau-1,\tau}^{H} \tag{5}$$

For the MPID tests, let $P\left(p^s, p^r, q^s, q^r\right)$ denote the price index between periods s and r with prices p^s and p^r and quantities q^2 and q^r. The multiperiod identity test for a chained index of T periods is then

$$MPID \text{ test value} = P\left(p^1, p^2, q^1, q^2\right) P\left(p^2, p^3, q^2, q^3\right) \cdots P\left(p^{T-1}, p^T, q^{T-1}, q^T\right) P\left(p^T, p^1, q^T, q^1\right) \tag{6}$$

which should equal 1. If not, the index is said to have chain drift under the definition which is non-circularity. The MPID test value gives a measure of the non-circularity. This was made for the chained Törnqvist indexes for the three imputation types as the above.

2.2 Bootstrapping

Overfitting is a possibility that needs to be tested for these regressions, since there are a very large number of variables. Overfitting occurs when so many degrees of freedom are used by the variables that the coefficients and predictions have such a high variance that they are can't be relied on for a certain purpose. If variance is a problem, the typical solution is to use one of many methods (including 'machine learning' methods) to reduce variance at the cost of additional bias. The purpose here is construct price indexes, and as Pakes (2003) points out, the predictions for prices only matter for how the index is affected. Bias becomes more important over time than variance for price indexes, since variance averages out over time, while bias accumulates. Therefore, if variance is above a unacceptable threshold at a certain time for the index levels, reducing bias should take precedence over variance.

Fifty bootstrapps were done for every goods category. For each bootstrap, all items that were ever in the sample were randomly sampled with replacement, a new regression was run every month with the bootstraped sample, and a new full imputation hedonic index series was made. The mean and standard deviation of these index levels was calculated for each period, and a near 95% (95.4%) confidence interval was made by adding and subtracting two standard deviations from the mean for each month.

3 Chain Drift

3.1 Methods

The CCDI method is a multilateral method often used with transactions data. For a given window of periods T, it makes unnormalized index levels ρ_t for each period in the window by taking the average Törnqvist index for that period and every other period in the window, and then normalizing the levels by the first period in the data to make the index level π_t,

$$\rho_t = \left[\Pi_{\tau=1}^{T}\Pi_i \left(\frac{p_{it}}{p_{i\tau}}\right)^{\frac{1}{2}(s_{i\tau}+s_{it})}\right]^{\frac{1}{T}} \tag{7}$$

$$\pi_t = \frac{\rho_t}{\rho_1} \tag{8}$$

This is the same as the GEKS (Gini (1931); Elteto and Koves (1964); Szulc (1964)) index, except that it uses the Törnqvist formula instead of the Fisher formula for bilateral indexes.

This will be exactly circular if the entire data range is used. However, for a long time span, this means they will be using long direct indexes as inputs that are poor Divisia approximations and have fewer goods common between the base and current periods, either losing goods or requiring more price predictions of missing prices. The common solution used by statistical agencies is a rolling window index, as proposed by Ivanic, Diewert, and Fox (2011). Every period the base period moves forward, so that the CCDI indexes are made for a window of the same length. Many splicing methods have been proposed, but as Fox, Levell, and O'Connell (2024) show, in practice they make little difference. Therefore in this paper, I only use the movement splice of IDF, which take the inflation rate from the last two period of the most recent window and multiplies (or splices) it onto the last normalized rolling window level. As described in Diewert and Fox (2022), the normalized index level for period T+1, splicing in period T, is

$$\pi_{T+1}(T) = \left(\frac{\rho_T}{\rho_1}\right)\left(\frac{\rho_{T+1}^{*}}{\rho_T^{*}}\right) \tag{9}$$

where the asterisk (*) denotes the unnormalized levels constructed from the new rolling window.

4 Data

The data is the IRI Academic Dataset for 2001 through 2012. It contains 38 goods categories of grocery and drug store sales, from all large retail chains, in weekly unit value prices and total quantities for each UPC of goods. This paper focuses on only 14 of those goods, half of them food: cold cereal, carbonated beverages, coffee, deodorant, diapers, facial tissue, laundry detergent, mayonnaise, peanut butter, paper towels, razors, salty snacks, toothbrushes, and yogurt. In order to avoid using parts of the weekly unit value to construct monthly indexes, each four week period was aggregated to make 13 artificial 'months' for each year. IRI constructs enough characteristics variables, including a store identifier, to identify every good at each store it is sold at. For example, the cold cereal category has characteristics for store, volume equivalent, flavor/scent, sugar content, package, fiber info, fortification, and type of grain, and has about 1.5 million observations per 4-week 'month'.

5 Hedonic Index Bootstrapping Results

The Appendix shows the mean bootstraped index and confidence interval for the 14 goods categories. About half have very tight intervals for all months, carbonated beverages, cold cereal, peanut butter, yogurt, deodorant, mayonnaise, and laundry detergent. For the other categories, the intervals are tight for almost all months, except for one or two months, usually January (first 4 weeks of the year), where the bootstraped indexes diverge, with some continuing the same path and others making a break, changing the mean and greatly increasing the variance. This divergent month is often the same across these categories, such as month 79 (January 2007) for diapers, facial tissue, coffee, and toothbrushes. For the vast majority of months the indexes do not diverge, which is not consistent with typical overfitting, since the results are very rarely sensitive to small changes in the data. Nevertheless, the divergent months could be because of some unusual price setting behavior for certain months, and will require more study.

6 Multilateral Index Results

6.1 CCDI Over Different Window Lengths

The Appendix shows the final CCDI index levels, at month 156, for 24 different window lengths from 2 months, which is a standard monthly chained Törnqvist index, up to 156 months, which is the full span of time, completely circular, and not a rolling window index. Three different imputations methods are shown: (1) the raw, not imputed data; (2) imputing prices for only the nonmissing values; (3) full imputation, for both raw and missing prices. Figure 5 in the appendix also shows the same imputation methods for the MPID test, which adds the first period on the end of the data, for the same window lengths.

If we use the MPID test as the measure of chain drift, most of the raw indexes show significant negative drift that, on average, shrinks with a longer rolling window, until the drift disappears, by construction, for the full window. But the path to circularity is far from straight. A common pattern is that after about 3-9 months, the drift grows worse with a longer window, such as for coffee, paper towels, salty snacks, toothbrushes, and to a smaller extent peanut butter and yogurt. It doesn't begin to shrink again until the window length is at least 2-8 years. For cold cereal, facial tissues, laundry detergent, and mayonnaise, the drift is still a major problem and doesn't start to improve until after a window of over two years.

The nonmissing imputation levels are usually very close to the raw index levels, except for very short windows, and is actually more likely to be higher than lower. They are always 'reasonable' or at least more 'reasonable', meaning it gives less extreme inflation rates, unless there is a divergence as shown in the graphs. It makes a major reduction in MPID measured drift, improving it in the short windows for all goods except paper towels and yogurt, and then only making it slightly worse. In cold cereal and carbonated beverages, it effectively fixes it entirely.

Doing full imputation typically makes a large difference in the index levels, 9 out of 14 goods having lower final levels for most window lengths. The 2 month chained index levels are at least as 'reasonable' as the raw and nonmissing indexes, and usually more so. Aside from a deflation rate of 14% over the 12 years for facial tissues, there is no deflation less than 5% unless there is a divergence as shown in the graphs, which is an indicator that something uncharacteristic happen in those months. The full window index levels have a much smaller difference with the 2 month chained levels, possibly because full imputation chained indexes may have less total drift.

Oddly, the full imputation indexes actually have the opposite drift pattern than the raw data for about half of the goods. For 6 of the goods, increasing the window length from 2 months (typical chained) to 9 months makes the chain drift worse, and only for three goods, cold cereal, toothbrushes, and mayonnaise, does it make more than a slight improvement. About half of the goods switch from more(less) drift to less(more) for some range of longer windows. This is very odd, since it would be expected that longer rolling windows should always reduce drift since they do more smoothing. However it should be kept in mind that, as shown in certain months in the bootstrapping results, there could be jumps in some of the full imputation indexes that affect these conclusions.

Overall, moving to a 6 or nine month window makes a big difference for the indexes, but it's only sometimes better and sometimes worse. Moving to an even longer window up to 2 years usually makes little difference, and is also just as likely to have worse drift than better.

The improvement in drift from the hedonic imputation indexes overall, and especially in the 2 month chained indexes, can be explained by the smoothing effect hedonic imputation has on prices. The hedonic indexes effectively refine the goods, making consumer preferences over characteristics instead of a UPC defined good. The lower drift of the nonmissing imputed indexes show the

effects of this smoothing without the added complication of the new and exiting items. When there is a sale, only those items on sale have a large price reduction in the raw data. But the hedonic indexes replace those sale prices with predicted prices based on the characteristics coefficients that are estimated from all items, whether on sale or not. Since the sales are not on characteristics themselves, this removes much of the price bouncing that is the underlying cause of chain drift. Unless all items with the same characteristic are on sale in the same month, the predicted price will fall much less than the raw sale price. The fact that some items with that characteristic are on sale will lower that characteristic's coefficient in that month, but the predicted price will still be much less volatile than the raw price. The table shows the correlations between raw and predicted prices for all the categories. The correlations vary from .2454 to .4676, and have a mean of .3554, showing a significant amount of smoothing.

Correlations Between Raw and Predicted Prices

Item	Correlation
cold cereal	.3204
mayonnaise	.4676
coffee	.3915
carbonated beverages	.3004
peanut butter	.4531
razors	.4152
deodorant	.2837
facial tissue	.3861
laundry detergent	.3642
diapers	.3424
tooth brushes	.2739
salty snacks	.2454
paper towels	.3785
yogurt	.3616

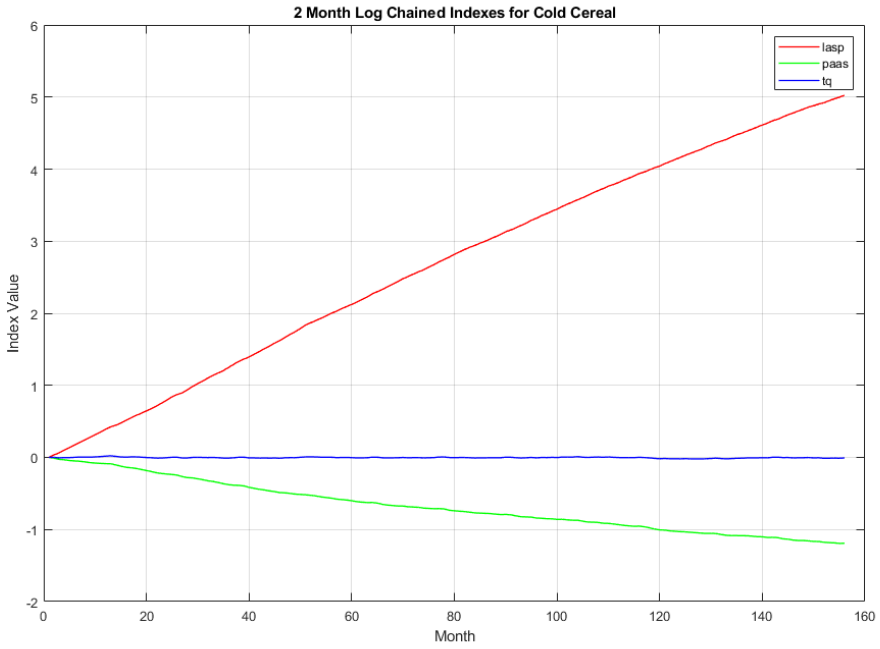
6.2 Laspeyres-Paasche Indexes

However, a simpler explanation of the odd results of the MPID tests is that the test are unreliable. In other words, the MPID test itself, and the multilateral indexes, fail the reasonability test. After all, the longer indexes that make up the windows are less reliable approximations and require more imputations for new and exiting goods than the monthly chained indexes. Even when there is not price bouncing the direct Törnqvist can diverge from the chained, and the chained is a more reliable index.

If we can't use the full window multilaterals or a full period direct index as the gold standard, we need another estimate of chain drift. As suggested in Hill (2006), since the Laspeyres and Paasche indexes bound a COLI, we can use the Laspeyres-Paasche spread as a measure of drift - a tight spread leaves little room for drift. However, simply using chained Laspeyres and Paasche indexes in this data leaves spreads that are too wide to be useful. For example, the

figure below plots the log chained Törnqvist, Laspeyres, and Paasche indexes for cold cereal as an example.

Chained Törnqvist, Laspeyres, and Paasche Indexes for Cold Cereal



Clearly, the drift in the Laspeyres and Paasche indexes is far too wild to make useful bounds.

However, we can construct CCDI/GEKS style multilateral Laspeyres and Paasche indexes. Since multilaterals reduce chain drift, the multilateral Laspeyres-Paasche indexes could provide insight on drift. Since the Laspeyres and Paasche indexes are not transitive, meaning that the index from period a to b is not the reciprocal of the index from b to a, the full window GEKS index will not be strictly circular by construction. Also, the 2 month rolling window Laspeyres and Paasche indexes are not the same as the monthly chained version of them because the GEKS procedure averages them with a 1 for the two month window, shown in equation (7). But because the GEKS Laspeyres and Paasche indexes are averages of the bilateral indexes within the window, and the bilateral indexes are bounds on the bilateral COLIs, there may still be insight to be gained. Figures in the Appendix plot the GEKS Laspeyres and Paasche indexes and the CCDI Törnqvist indexes for the same window lengths as before, for the raw and full imputation hedonic indexes.

In general, the raw spreads are either small for all window or become tight for longer windows. This is what would be expected, since when there is no chain drift, monthly indexes should all be close approximations of the Divisia index and thus of the true COLI, shown in Kurtzon (2022). Oddly, for short or medium length windows, the Paasche index is above the Törnqvist or even Laspeyres. For the full imputation indexes, the spreads are much wider, often still wide at the full, non-rolling window length. The full imputation GEKS Paasche index is usually above the other indexes even for long windows.

7 Conclusions/Discussion

Using a hedonic index should be done for bias reduction of omitting new and exiting goods, avoiding unit values, and additionally this paper provides evidence that hedonics can also reduce chain drift, though probably not eliminate it, though there are a small number of problem months which require more investigation. Given the use of a hedonic index, the MPID tests imply that a rolling window multilateral index such as the CCDI is as likely to make drift worse as better unless the window was extremely long. But the odd behavior of the MPID tests could be due to the unreliability of the longer bilateral indexes that make up a window, even a short one, because they are poorer Divisia approximations and suffer from more product turnover. The Laspeyres-Paasche indexes show the beneficial effects of drift reduction of a CCDI index for the raw data by showing the index formulas converge, but when hedonics is used, it may be the fact that Laspeyres and Paasche indexes are not transitive and not perfectly circular within a window makes a much larger difference. Thus, the use of a multilateral index such as a CCDI will need more research if it is to be combined with hedonics.

8 References

1. Balk, B.M. (2005) "Divisia price and quantity indicies: 80 years after". *Statistica Neerlandica*, 59, 119–158.

2. Caves, Douglas W., Laurits R. Christensen, and W. Erwin Diewert (1982) "Multilateral Comparisons of Output, Input, and Productivity Using Superlative Index Numbers". *The Economic Journal*, 92, pp. 73-86.

3. de Haan, Jan and Frances Krsinich. (2014) "Scanner Data and the Treatment of Quality Change in Nonrevisable Price Indexes". *Journal of Business & Economic Statistics,* 32 : pp. 341-358.

4. Diewert, W.E. (1976) "Exact and superlative index numbers". *Journal of Econometrics*, 4, 115–145.

5. Diewert (1993). "The Early History of Price Index Research", in W.E. Diewert and A.O. Nakamura (eds.): *Essays in Index Number Theory, Vol. 1, Contributions to Economic Analysis* 217 (Amsterdam: North-Holland), pp. 33–65.

6. Diewert, W.E. and Kevin Fox. (2022) "Substitution Bias in Multilateral Methods for CPI Construction" *Journal of Business and Economic Statistics*, 40 : pp. 355-369.

7. Divisia, F. (1925) "L'indice monetaire et la theorie de la monnaie. Revue d'economie politique", 39, 842–861.

8. Elteto, O. and P. Koves (1964). On a Problem of Index Number Computation Relating to International Comparisons. Statisztikai 42 (10), 507-518.

9. Gini, C. (1931). On the circular test of index numbers. Metron 9 (9), 3-24.

10. Fox, Kevin, Peter Levell, and Martin O'Connell (2023) "Inflation measurement with high frequency data", Institute for Fiscal Studies Working Paper 23/29.

11. Feenstra, Robert and Matthew D. Shapiro. (2003) "High-Frequency Substitution and the Measurement of Price Indexes" *NBER volume* .

12. ILO. (2004) Consumer price index manual: theory and practice. Geneva: International Labour Organization, International Monetary Fund, Organization for Economic Co-operation and Development, Statistical Office of the European Communities, United Nations, The International Bank for Reconstruction and Development, The World Bank.

13. Ivancic, Lorraine, W. Erwin Diewert, and Kevin J. Fox. (2011) "Scanner data, time aggregation, and the construction of price indexes." *Journal of Econometrics*, 161: pp. 24-35.

14. Hill, R.J. (2006a) "When does chaining reduce the Paasche-Laspeyres spread? An application to scanner data". The Review of Income and Wealth, 52, 309–325.

15. —- (2006b), "Superlative index numbers: not all of them are super". Journal of Econometrics, 130, 25–43.

16. Kurtzon, Gregory. (2022) "How Much Does Formula vs. Chaining Matter for a Cost-of-Living Index? The CPI-U vs. the C-CPI-U" *Economic Inquiry* 60: pp. 645-667.

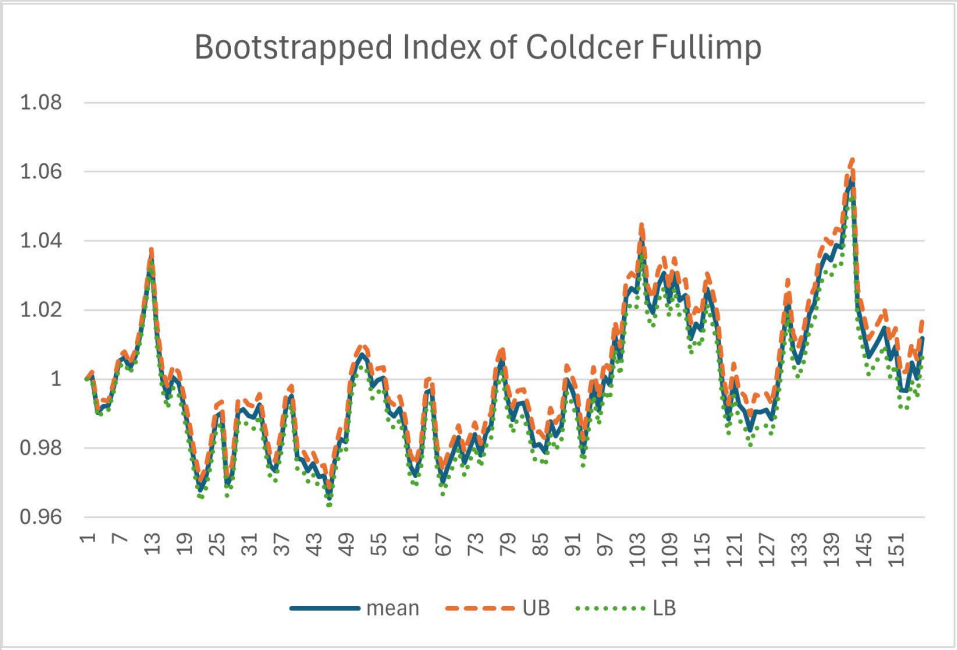
17. Melser, Daniel and Michael Webster. "Multilateral Methods, Substitution Bias, and Chain Drift: Some Empirical Comparisons". *Review of Income and Wealth*, 67 (2021): pp. 759-785.

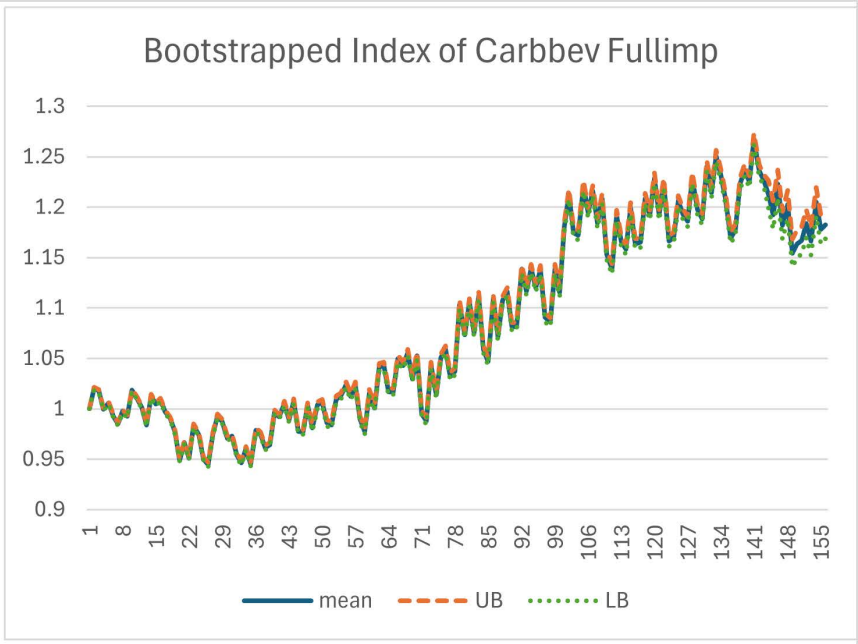
18. Pakes, Ariel. "A Reconsideration of Hedonic Price Indexes with an Application to PC's". *The American Economic Review*, 93 (2003): pp. 1578-96.

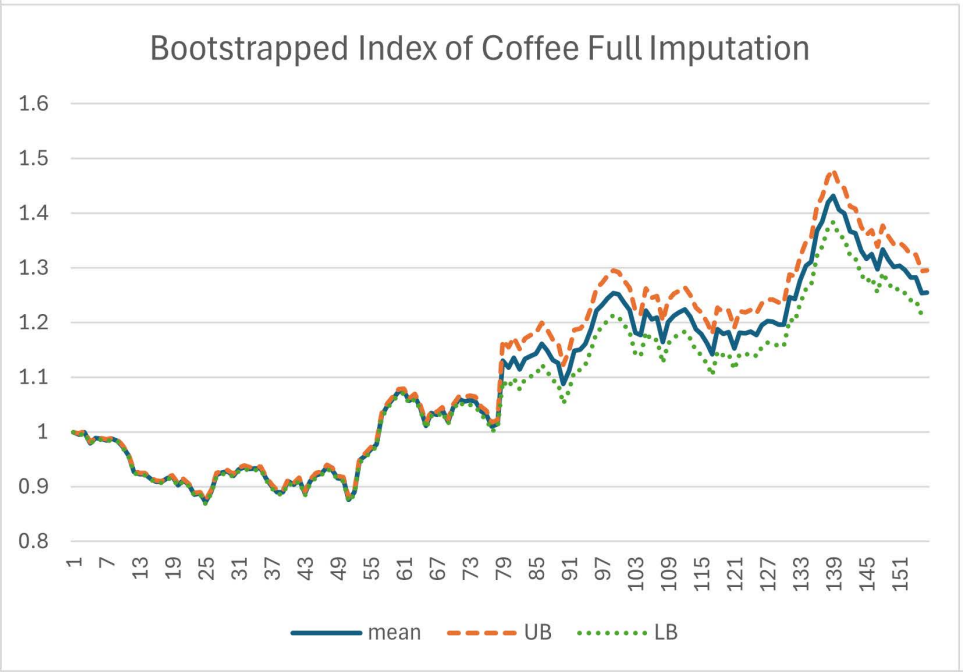
19. Reinsdorf, M.B. (1998) "Divisia indexes and the representative consumer problem". Presented at the Fourth Meeting of the Ottawa Group.

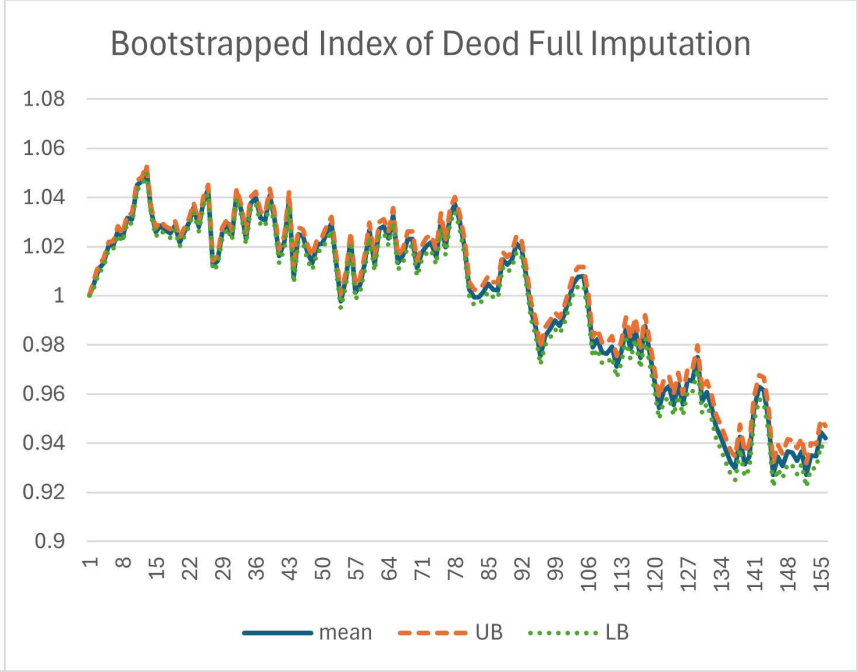
20. Szulc, B. (1964). Indices for Multiregional Comparisons. Przeglad Statystyczny 3, 239-254.

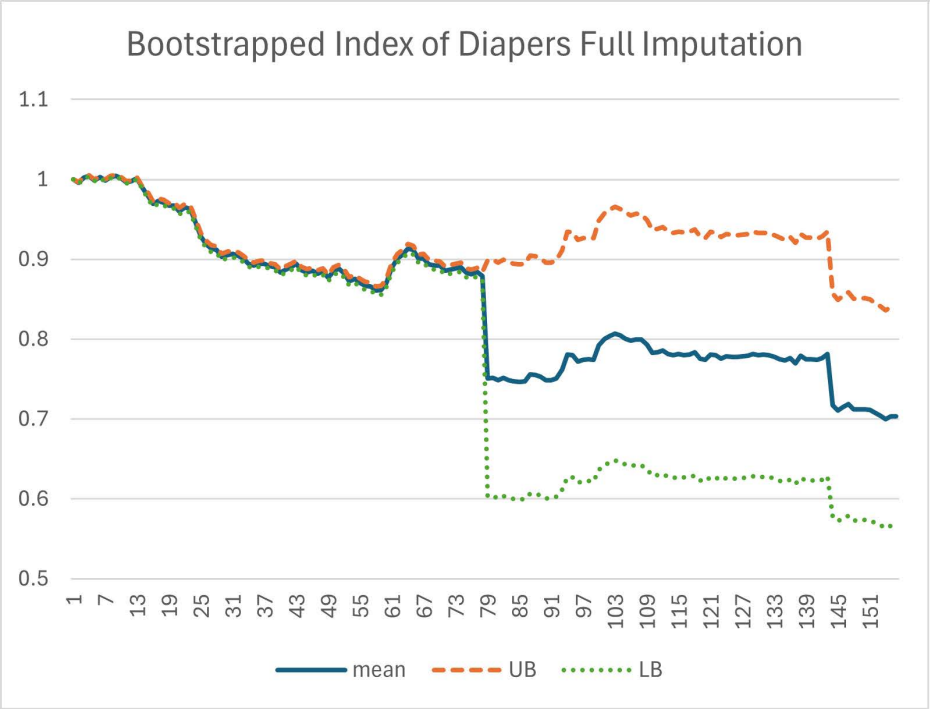
21. Walsh, C.M. (1901) *The Measurement of General Exchange Value.*

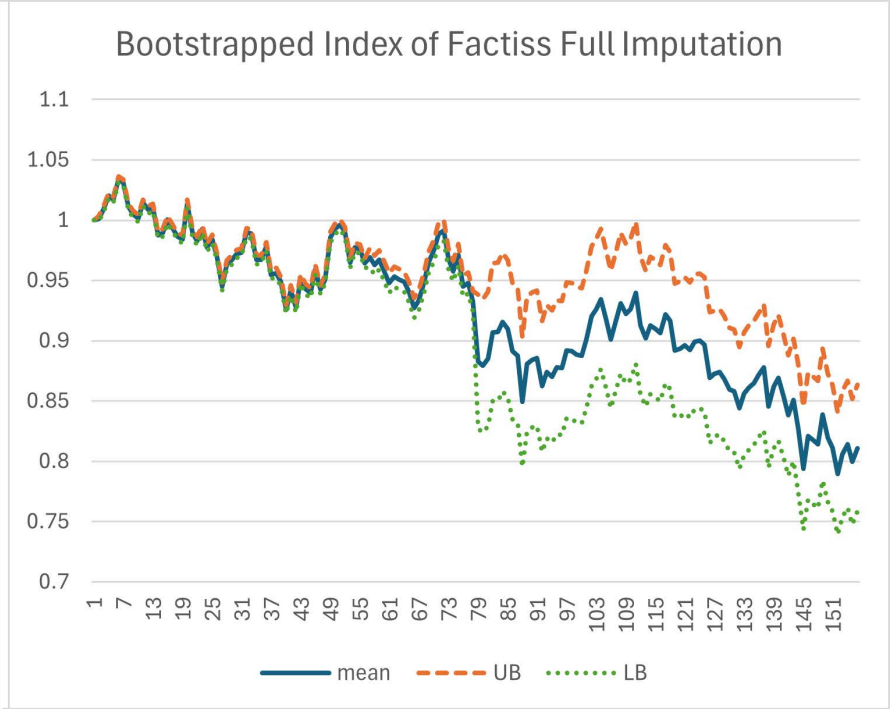

Bootstrapped Index of Coldcer Fullimp
1.08
1.06
1.04
1.02
1
0.98
0.96
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

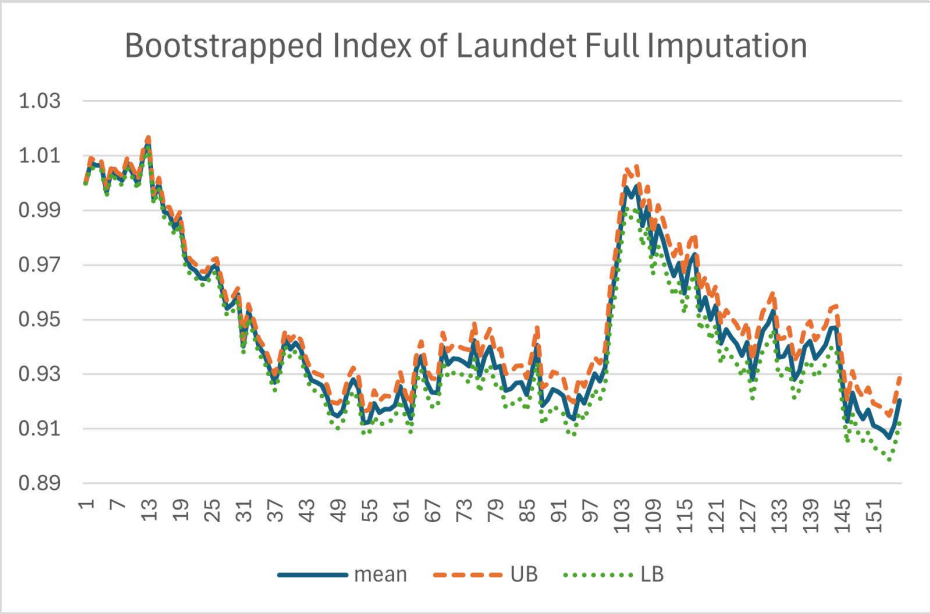

Bootstrapped Index of Carbbev Fullimp
1.3
1.25
1.2
1.15
1.1
1.05
1
0.95
0.9
1 8 15 22 29 36 43 50 57 64 71 78 85 92 99 106 113 120 127 134 141 148 155
mean
UB
LB

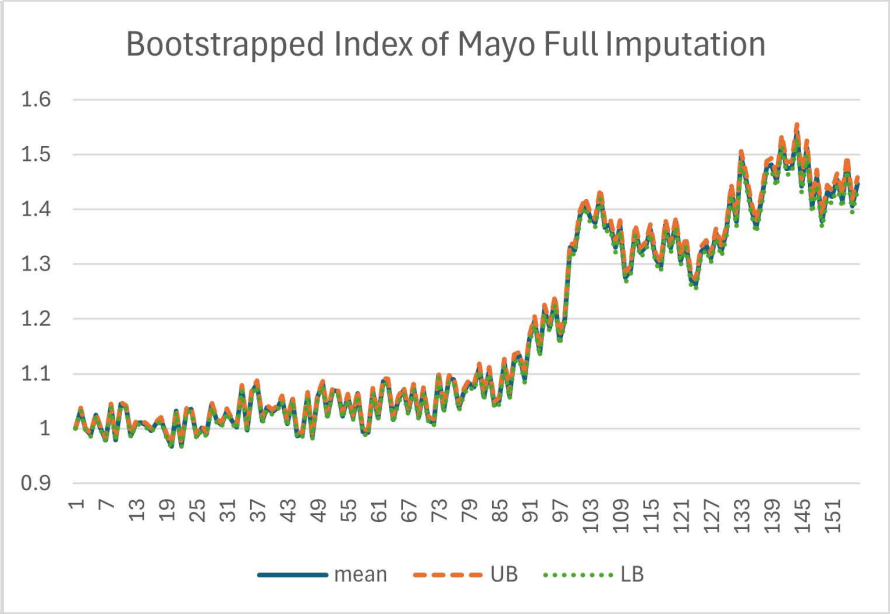

Bootstrapped Index of Coffee Full Imputation
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

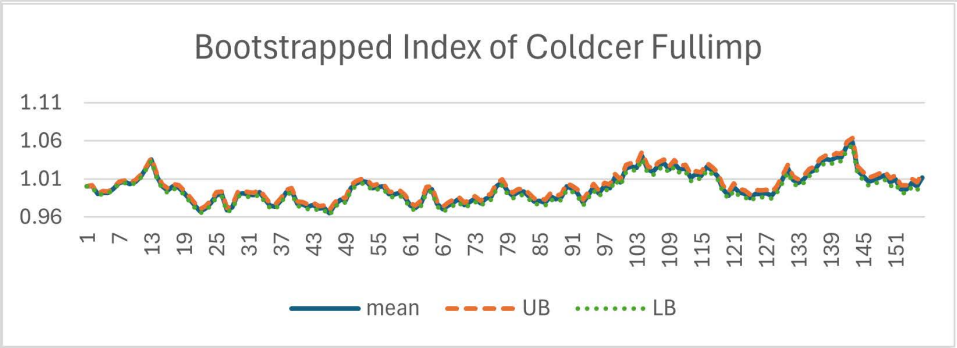

Bootstrapped Index of Deod Full Imputation
1.08
1.06
1.04
1.02
1
0.98
0.96
0.94
0.92
0.9
1 8 15 22 29 36 43 50 57 64 71 78 85 92 99 106 113 120 127 134 141 148 155
mean
UB
LB

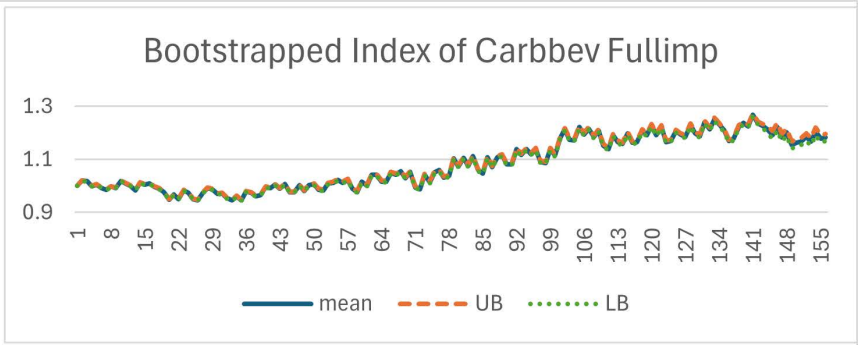

Bootstrapped Index of Diapers Full Imputation
1.1
1
0.9
0.8
0.7
0.6
0.5
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

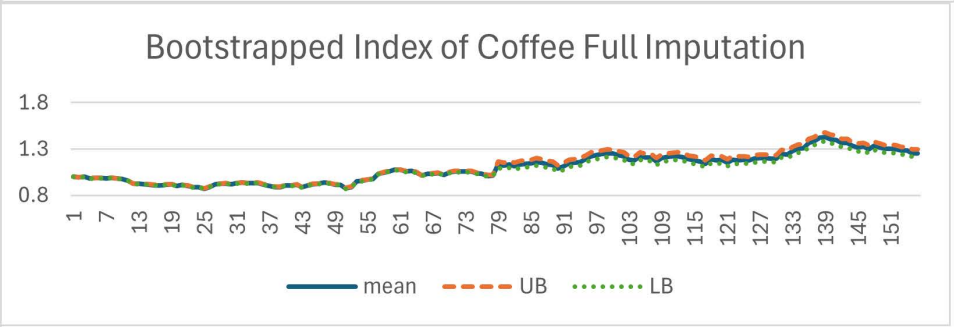

Bootstrapped Index of Factiss Full Imputation
1.1
1.05
1
0.95
0.9
0.85
0.8
0.75
0.7
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

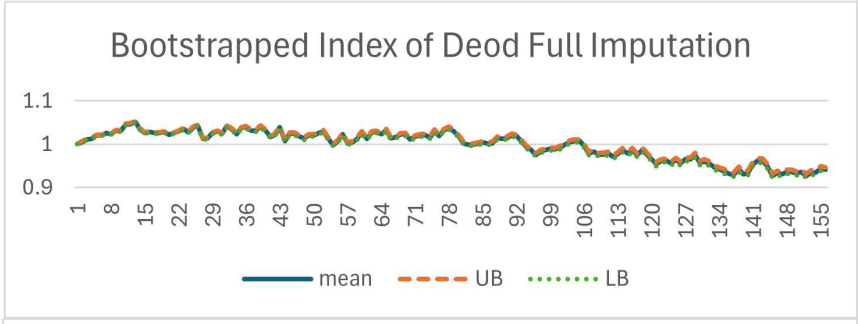

Bootstrapped Index of Laundet Full Imputation
1.03
1.01
0.99
0.97
0.95
0.93
0.91
0.89
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

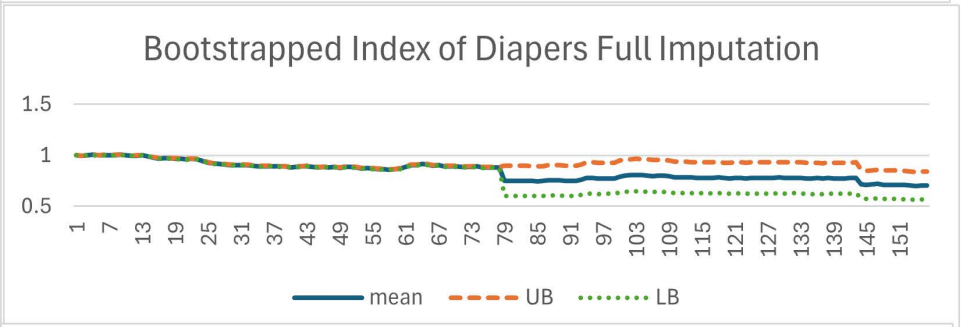

Bootstrapped Index of Mayo Full Imputation
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

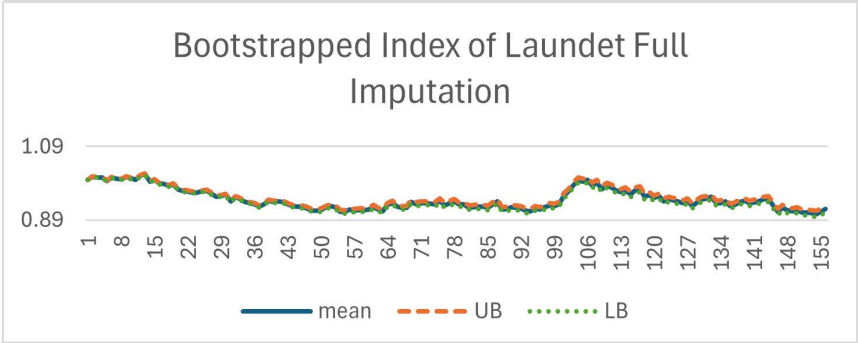

Bootstrapped Index of Coldcer Fullimp
1.11
1.06
1.01
0.96
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

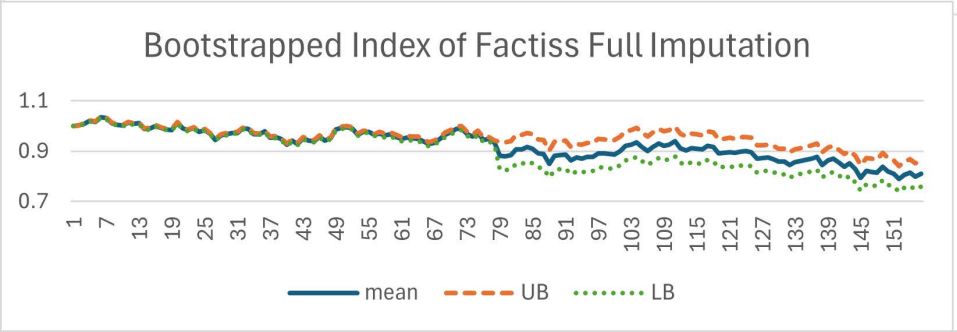

Bootstrapped Index of Carbbev Fullimp
1.3
1.1
0.9
1 8 15 22 29 36 43 50 57 64 71 78 85 92 99 106 113 120 127 134 141 148 155
mean
UB
LB

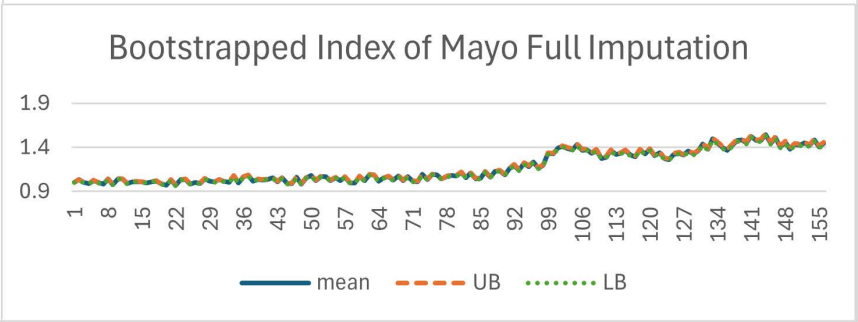

Bootstrapped Index of Coffee Full Imputation
1.8
1.3
0.8
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

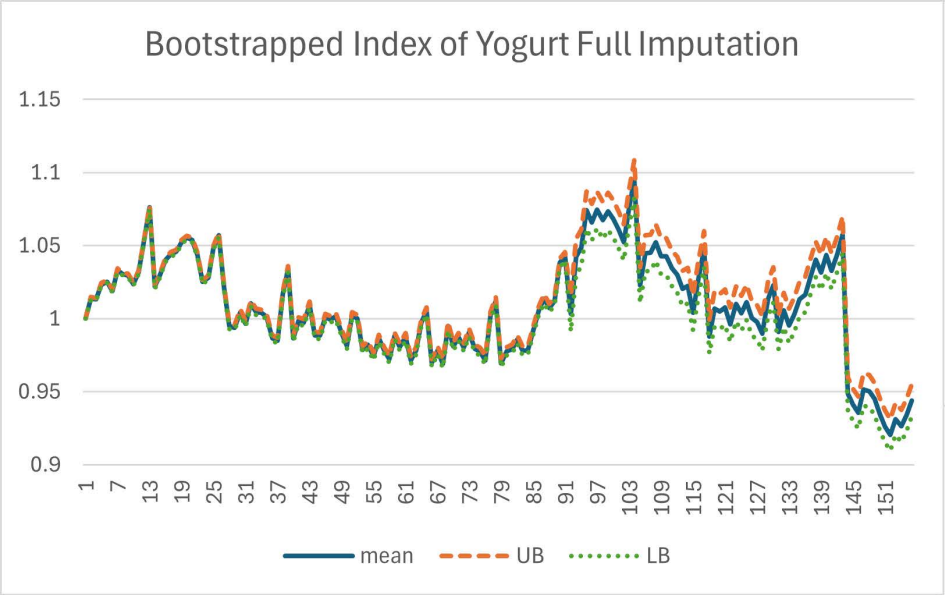

Bootstrapped Index of Deod Full Imputation
1.1
1
0.9
1 8 15 22 29 36 43 50 57 64 71 78 85 92 99 106 113 120 127 134 141 148 155
mean
UB
LB

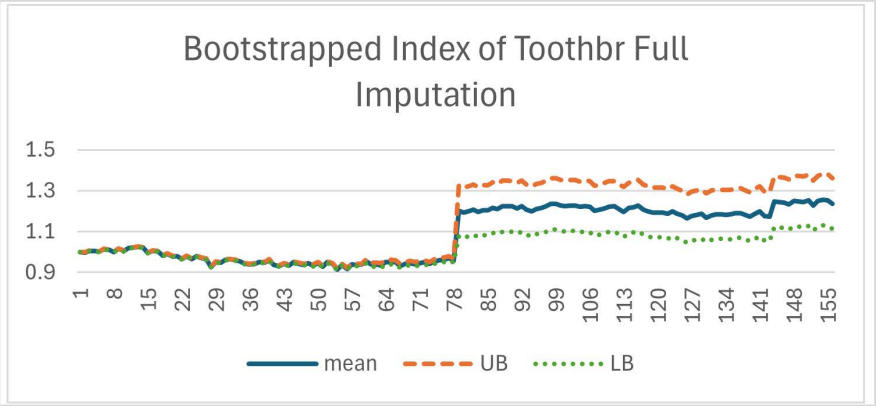

Bootstrapped Index of Diapers Full Imputation
1.5
1
0.5
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

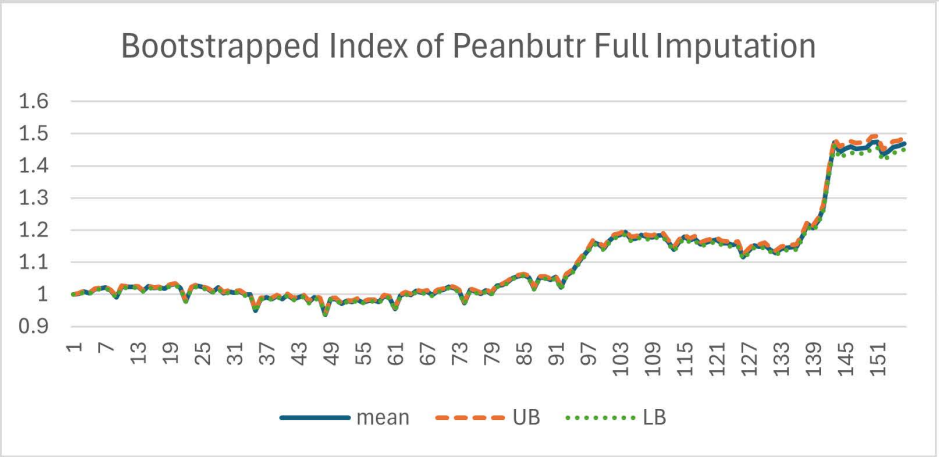

Bootstrapped Index of Laundet Full Imputation
1.09
0.89
1 8 15 22 29 36 43 50 57 64 71 78 85 92 99 106 113 120 127 134 141 148 155
mean
UB
LB

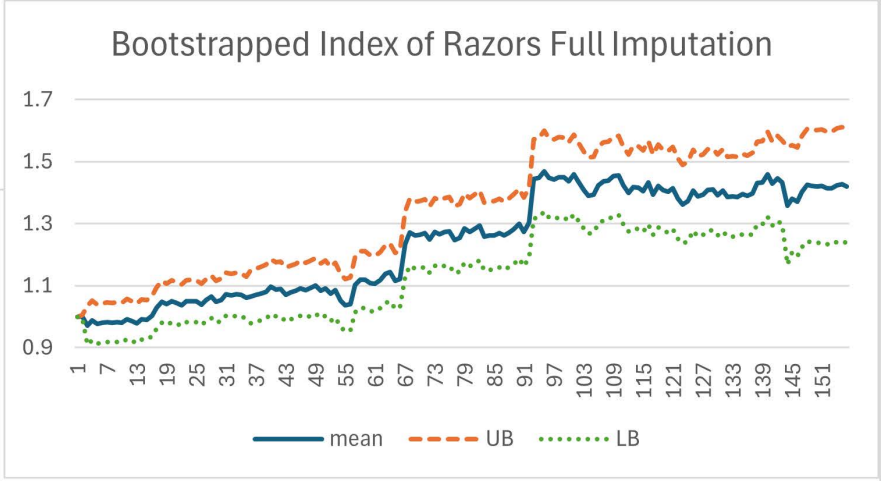

Bootstrapped Index of Factiss Full Imputation
1.1
0.9
0.7
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

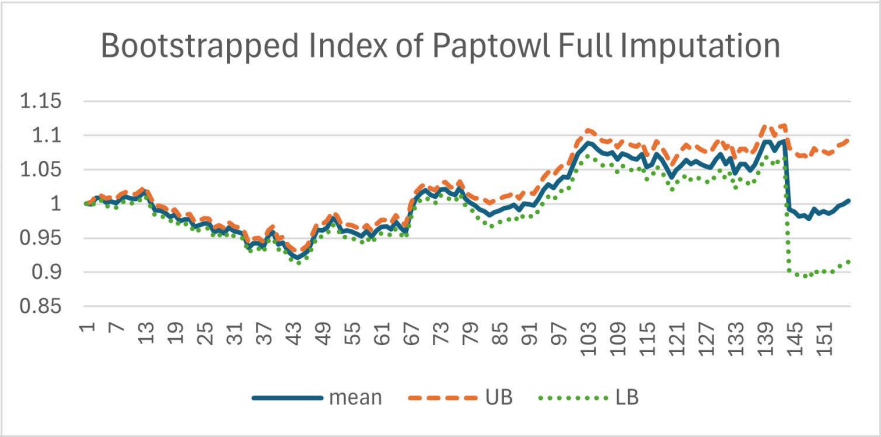

Bootstrapped Index of Mayo Full Imputation
1.9
1.4
0.9
1 8 15 22 29 36 43 50 57 64 71 78 85 92 99 106 113 120 127 134 141 148 155
mean
UB
LB

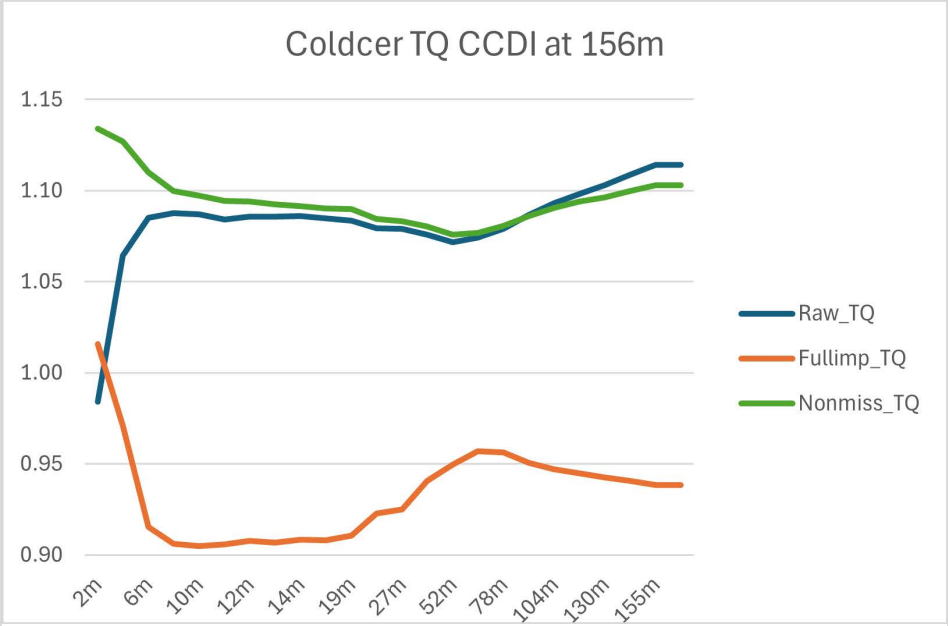

Bootstrapped Index of Yogurt Full Imputation
1.15
1.1
1.05
1
0.95
0.9
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

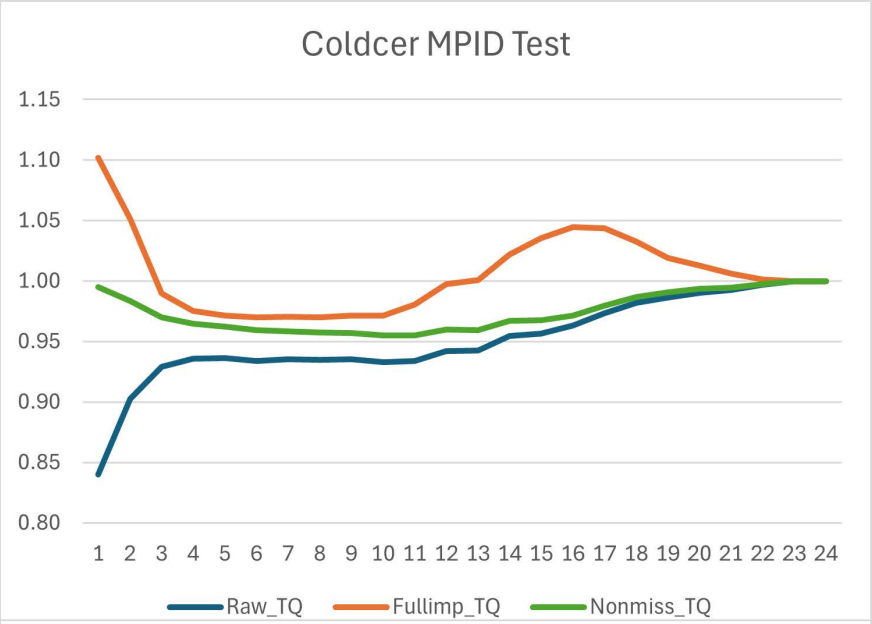

Bootstrapped Index of Toothbr Full Imputation
1.5
1.3
1.1
0.9
1 8 15 22 29 36 43 50 57 64 71 78 85 92 99 106 113 120 127 134 141 148 155
mean
UB
LB

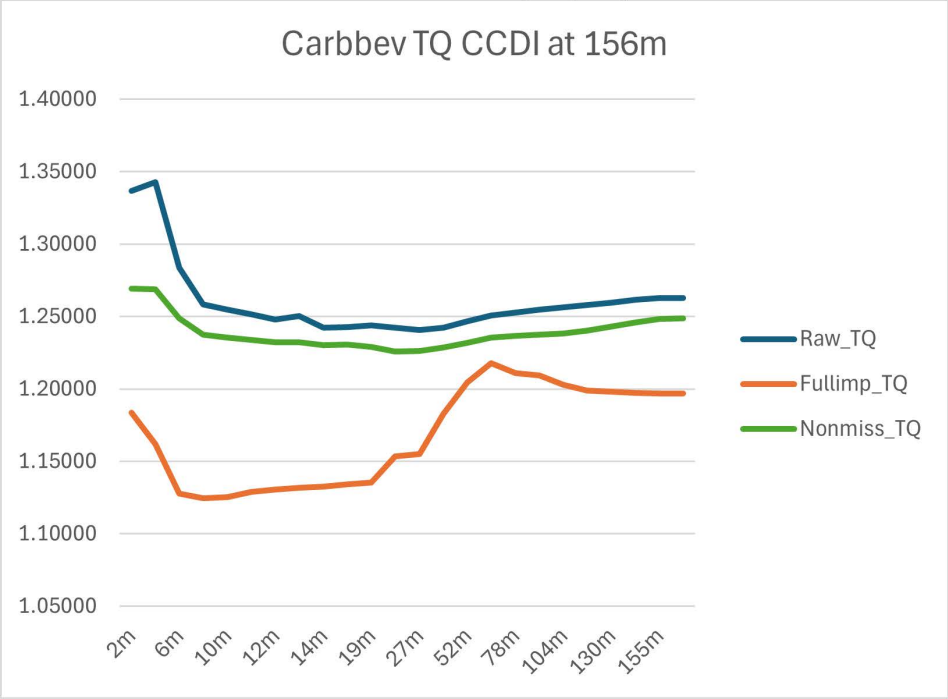

Bootstrapped Index of Peanbutr Full Imputation
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

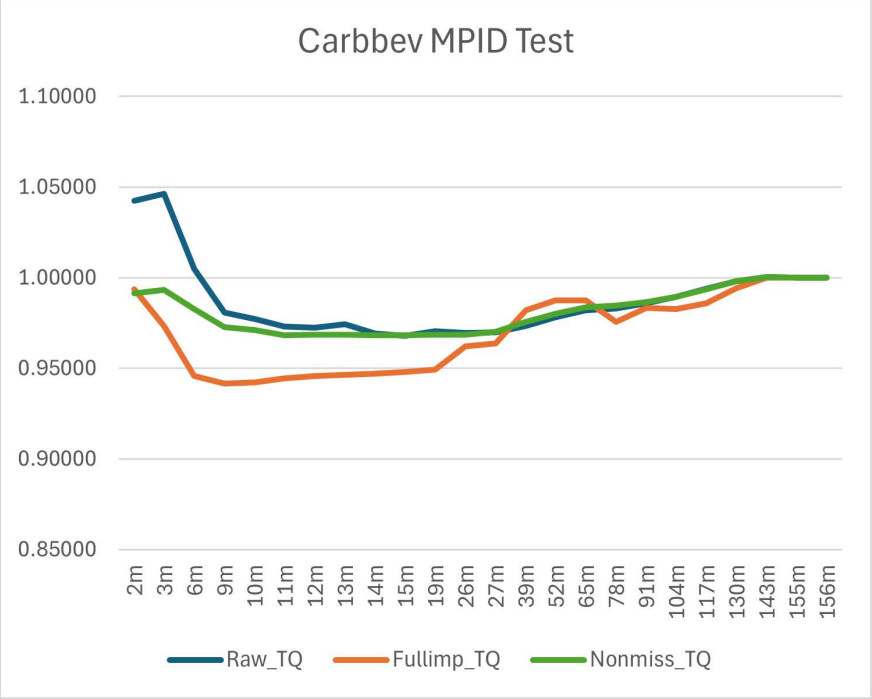

Bootstrapped Index of Razors Full Imputation
1.7
1.5
1.3
1.1
0.9
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

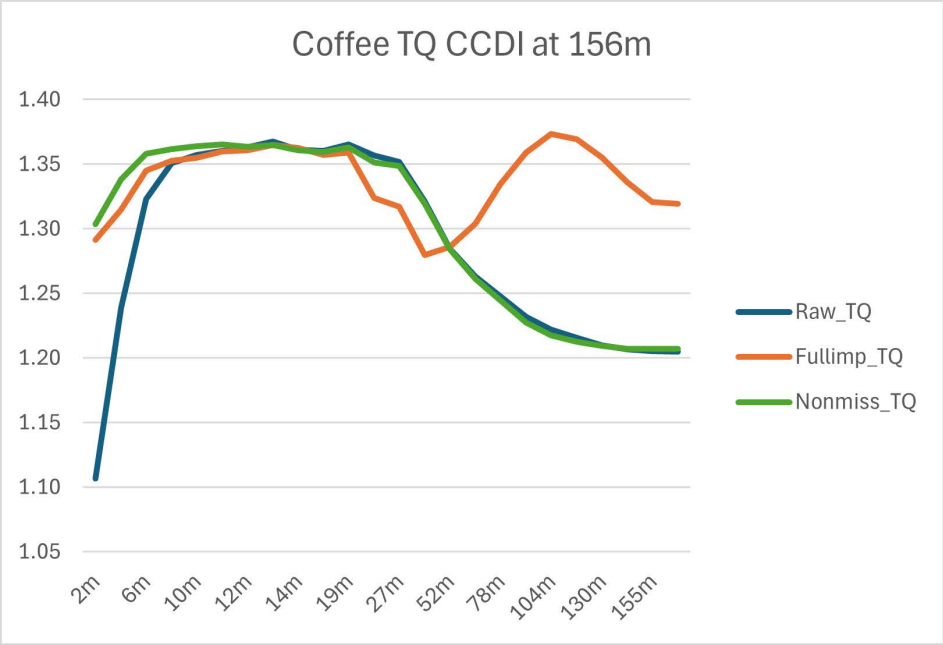

Bootstrapped Index of Paptowl Full Imputation
1.15
1.1
1.05
1
0.95
0.9
0.85
1 7 13 19 25 31 37 43 49 55 61 67 73 79 85 91 97 103 109 115 121 127 133 139 145 151
mean
UB
LB

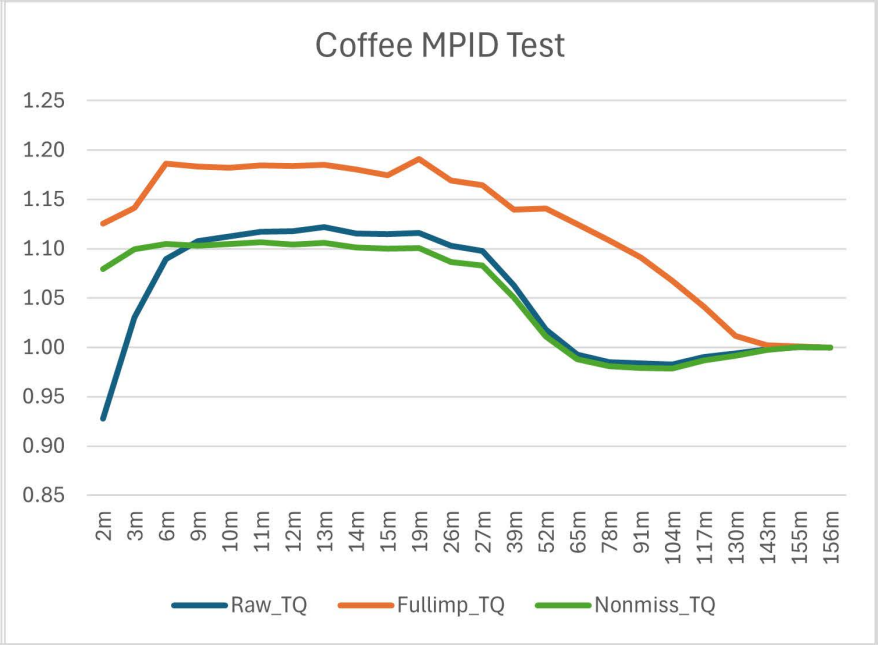

Coldcer TQ CCDI at 156m
1.15
1.10
1.05
1.00
0.95
0.90
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

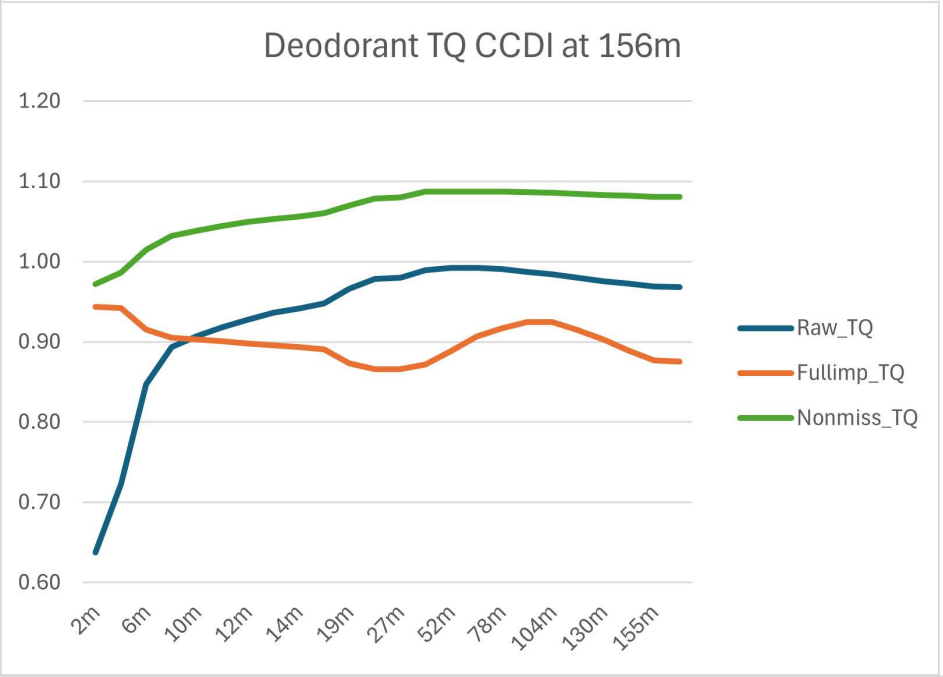

Coldcer MPID Test
1.15
1.10
1.05
1.00
0.95
0.90
0.85
0.80
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

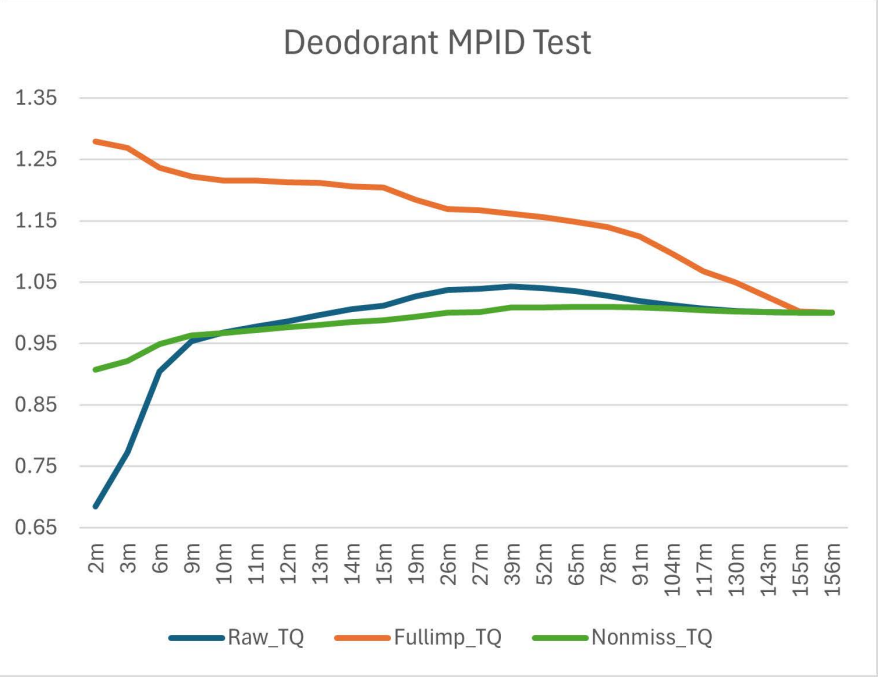

Carbbev TQ CCDI at 156m
1.40000
1.35000
1.30000
1.25000
1.20000
1.15000
1.10000
1.05000
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

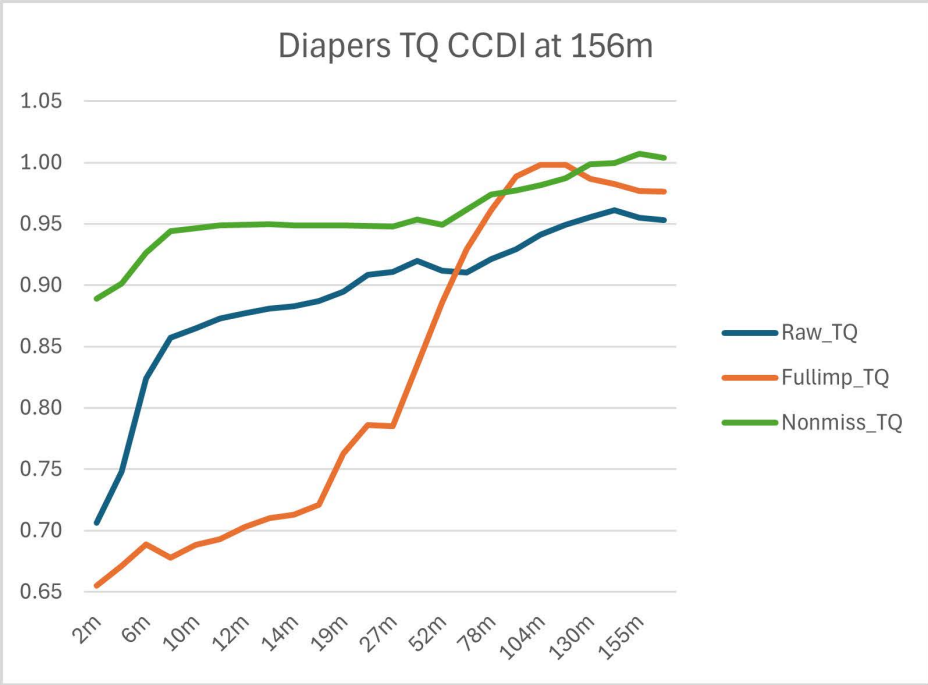

Carbbev MPID Test
1.10000
1.05000
1.00000
0.95000
0.90000
0.85000
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

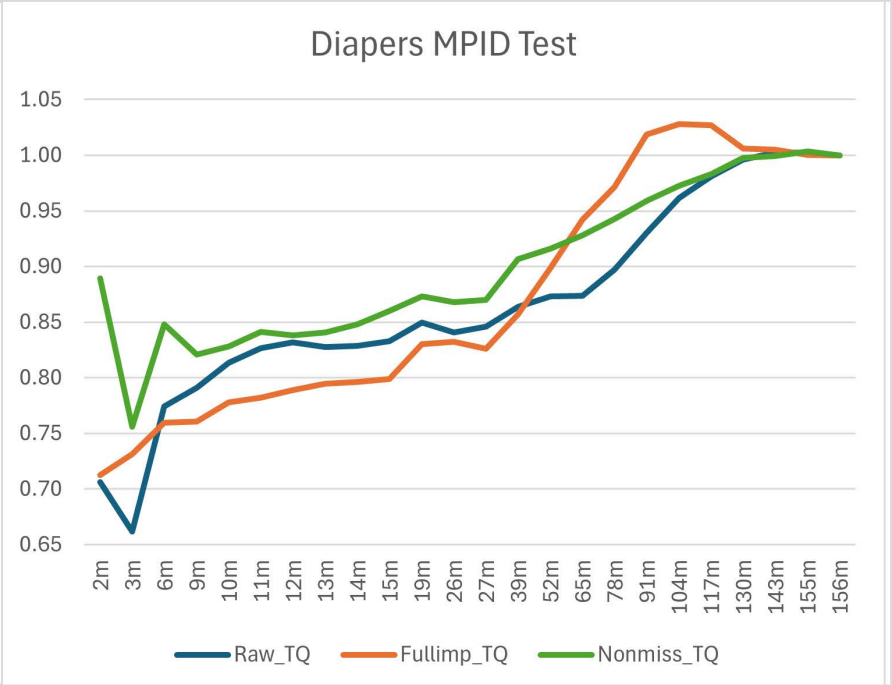

Coffee TQ CCDI at 156m
1.40
1.35
1.30
1.25
1.20
1.15
1.10
1.05
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

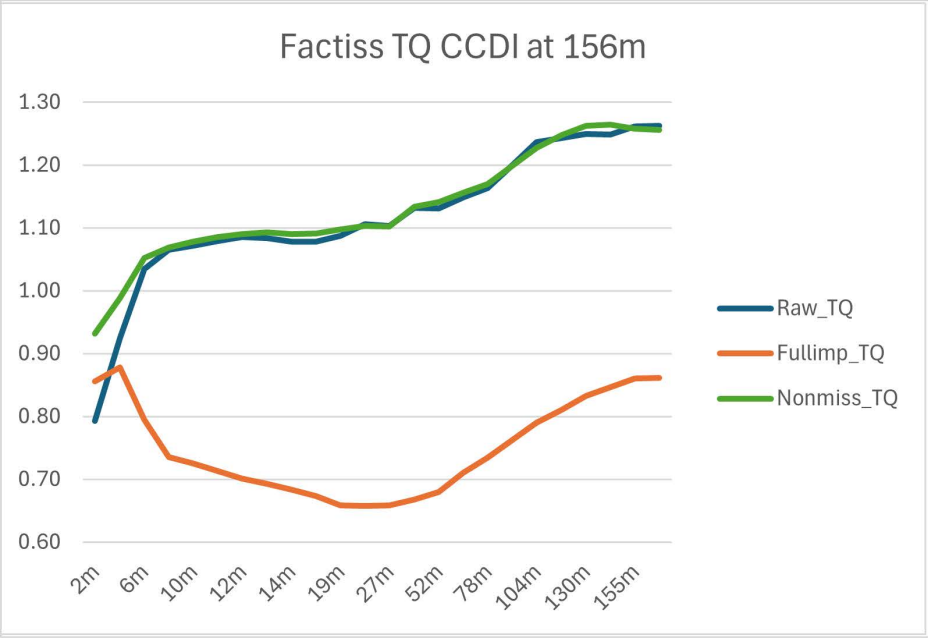

Coffee MPID Test
1.25
1.20
1.15
1.10
1.05
1.00
0.95
0.90
0.85
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

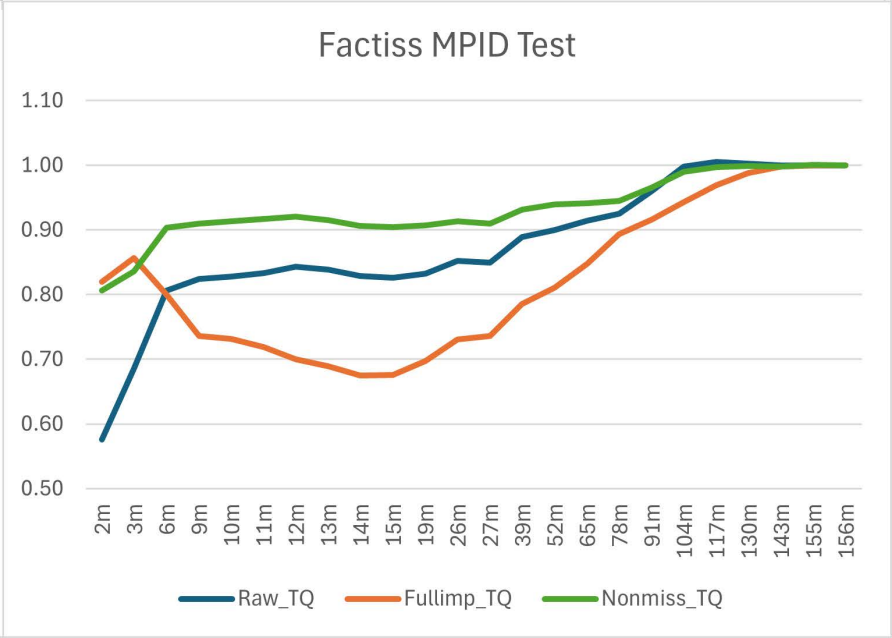

Deodorant TQ CCDI at 156m
1.20
1.10
1.00
0.90
0.80
0.70
0.60
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

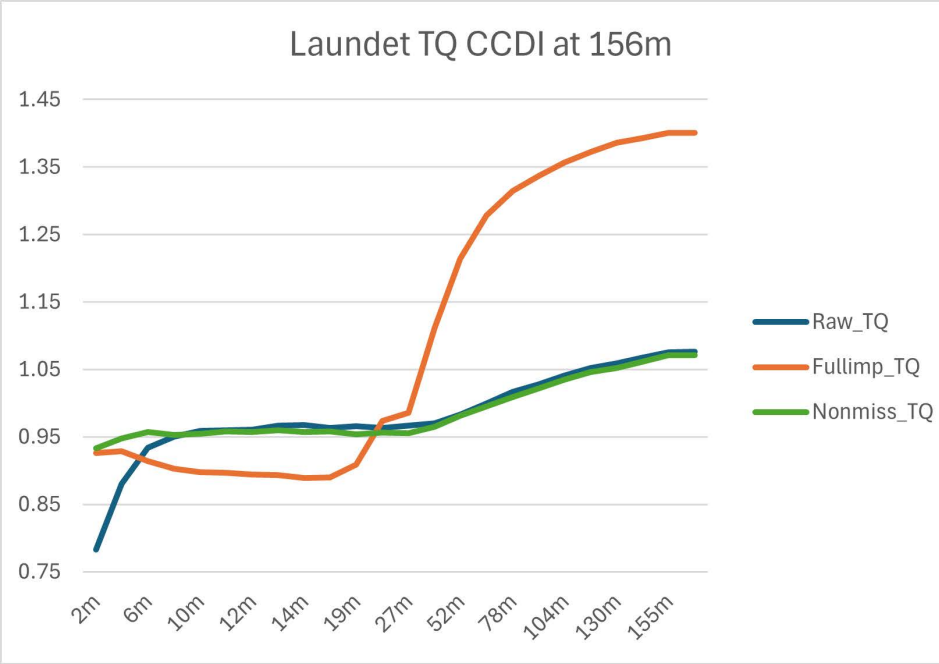

Deodorant MPID Test
1.35
1.25
1.15
1.05
0.95
0.85
0.75
0.65
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

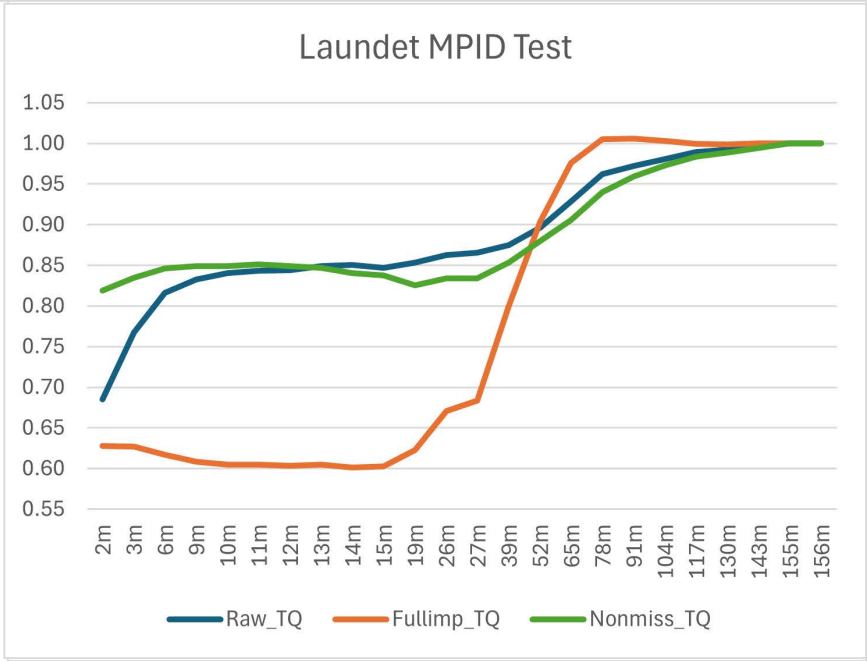

Diapers TQ CCDI at 156m
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

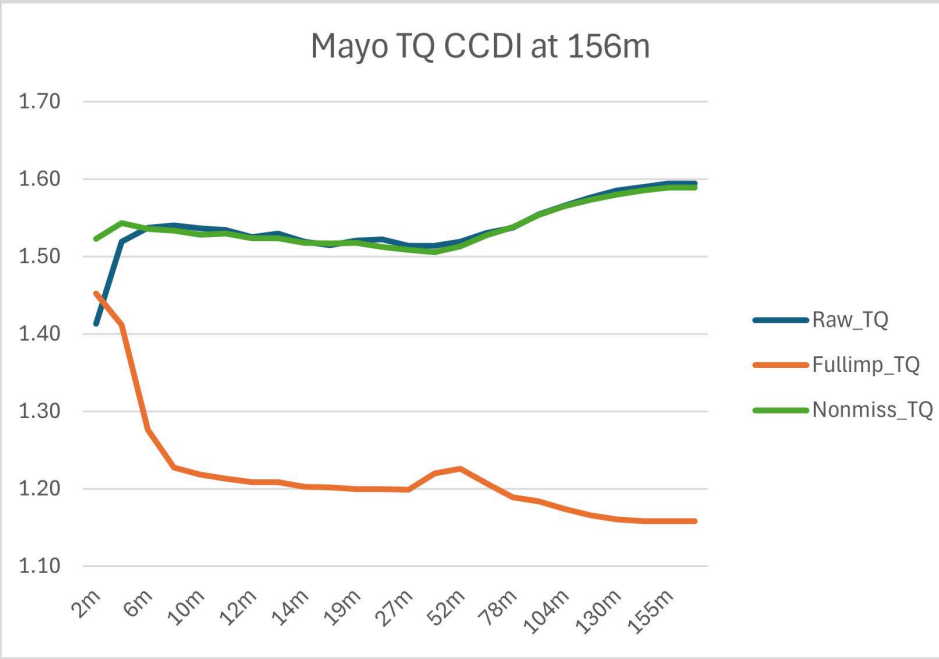

Diapers MPID Test
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

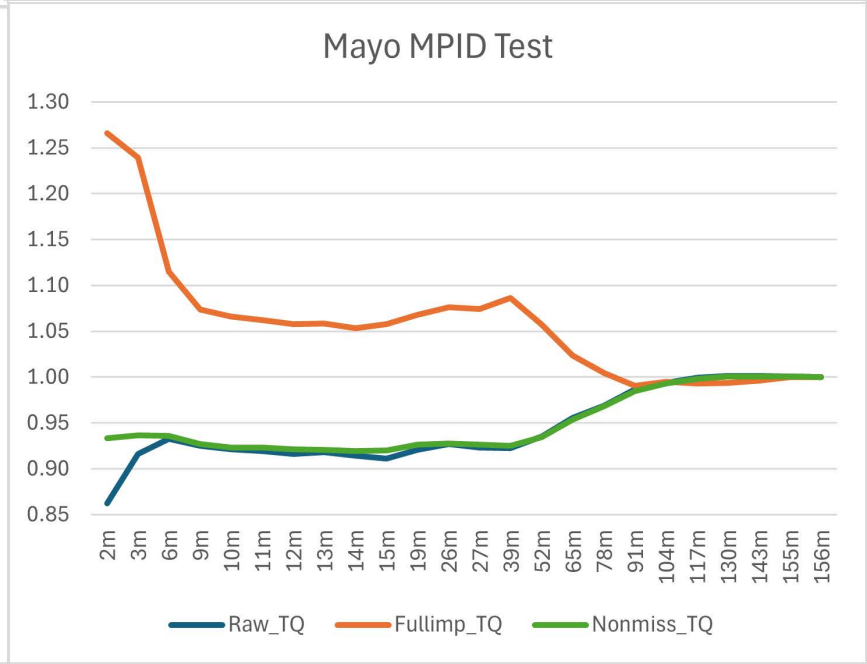

Factiss TQ CCDI at 156m
1.30
1.20
1.10
1.00
0.90
0.80
0.70
0.60
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

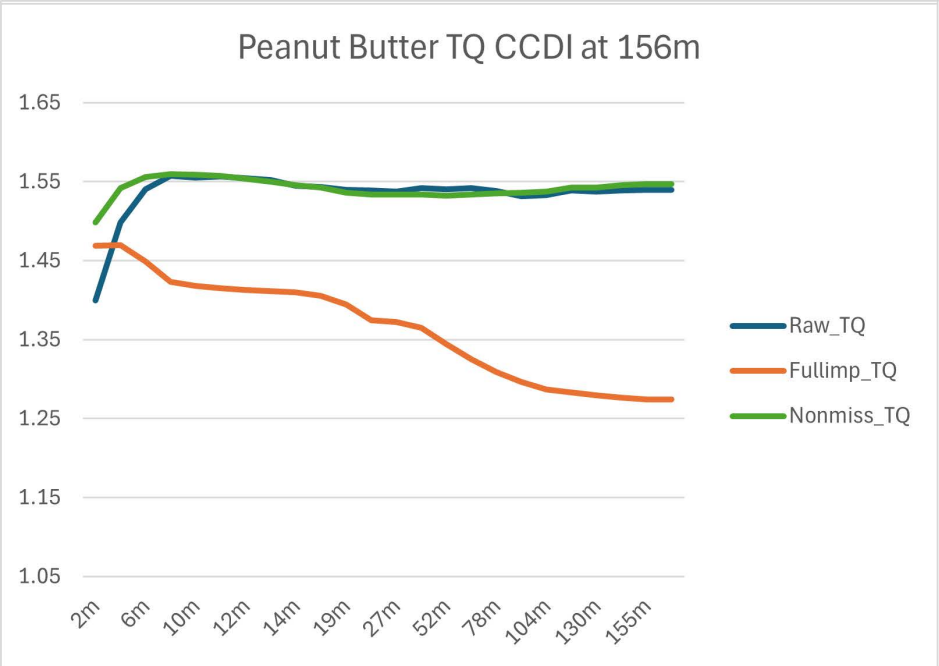

Factiss MPID Test
1.10
1.00
0.90
0.80
0.70
0.60
0.50
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

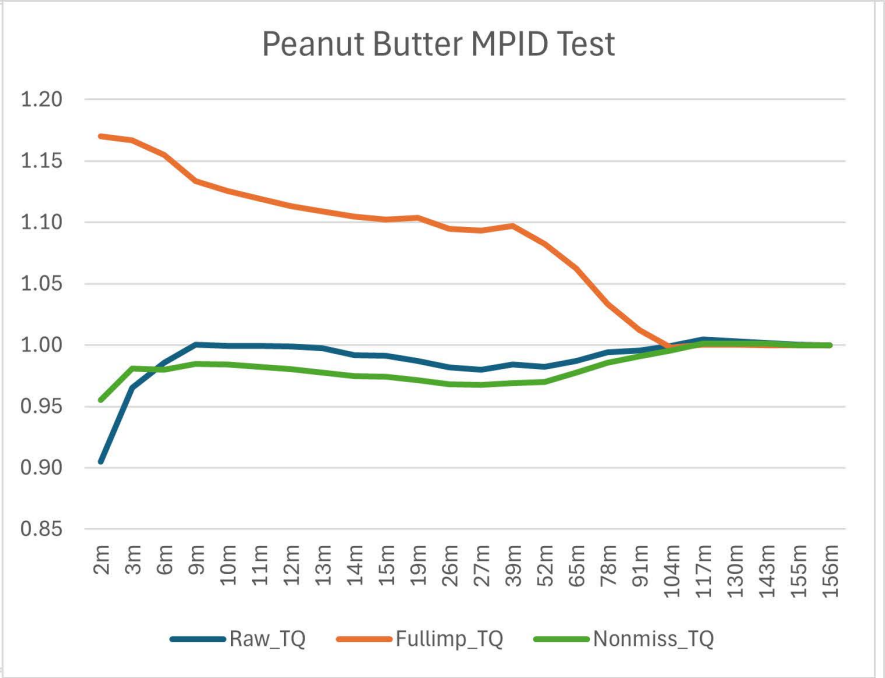

Laundet TQ CCDI at 156m
1.45
1.35
1.25
1.15
1.05
0.95
0.85
0.75
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

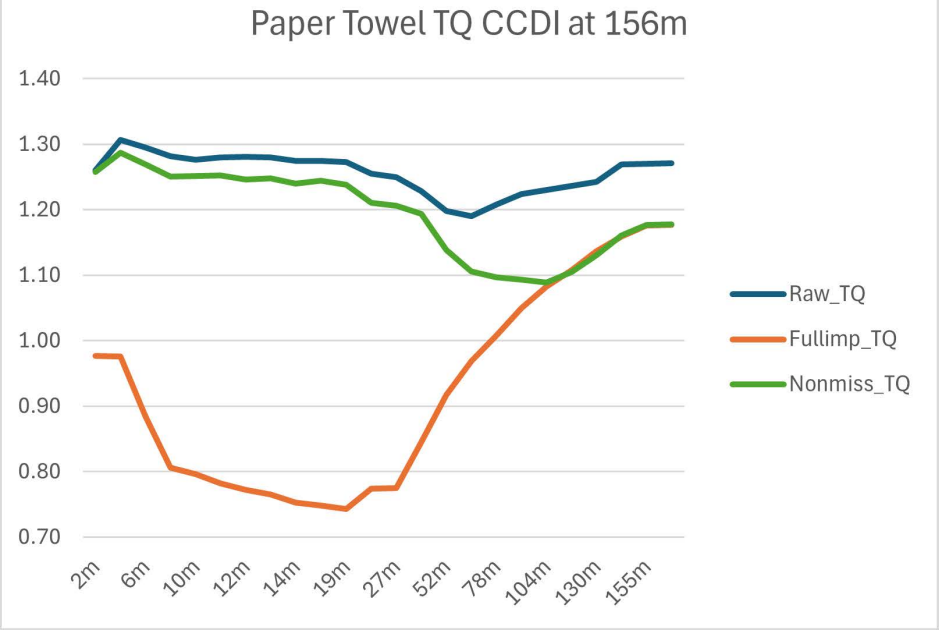

Laundet MPID Test
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

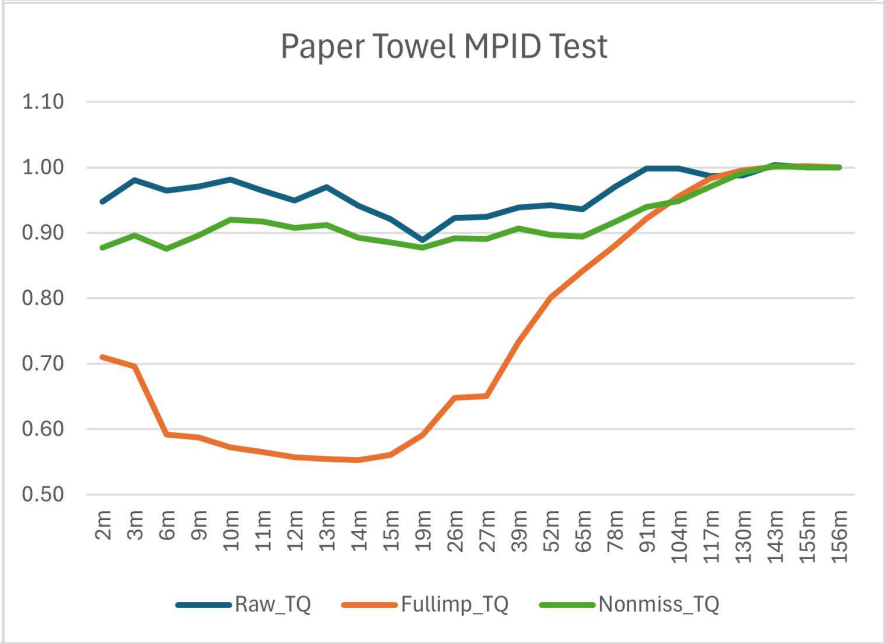

Mayo TQ CCDI at 156m
1.70
1.60
1.50
1.40
1.30
1.20
1.10
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

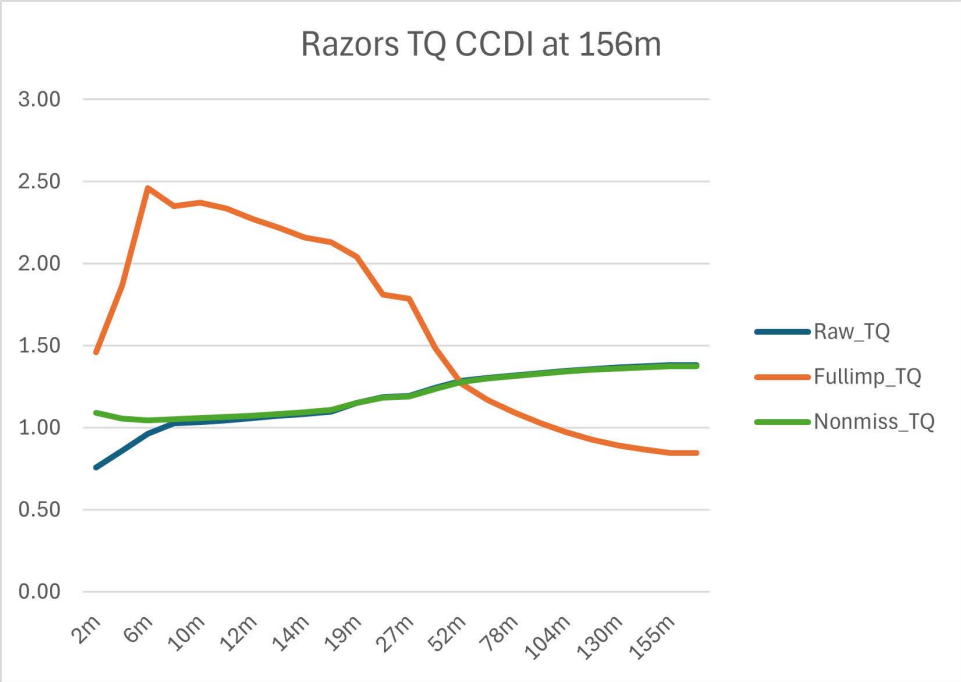

Mayo MPID Test
1.30
1.25
1.20
1.15
1.10
1.05
1.00
0.95
0.90
0.85
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

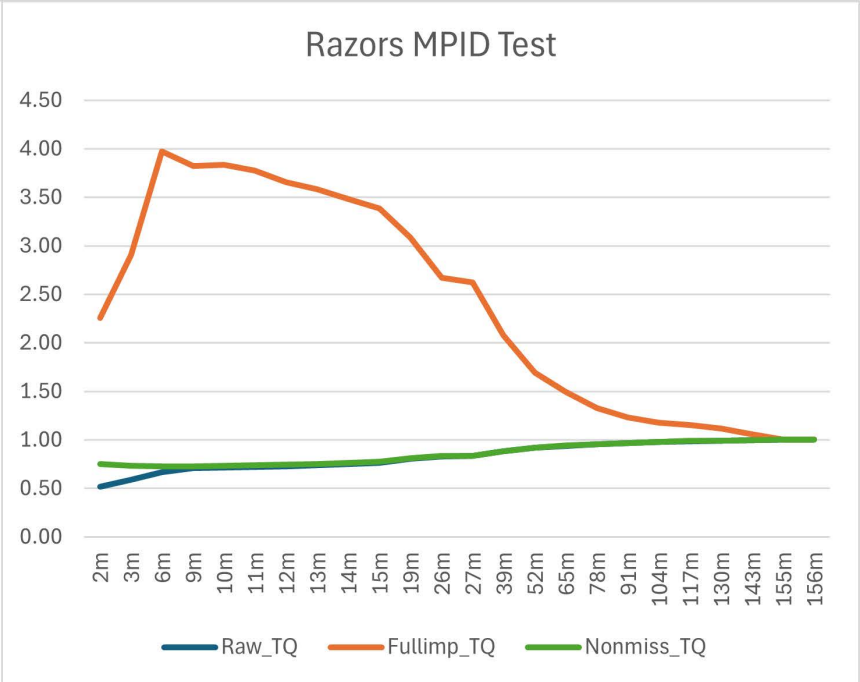

Peanut Butter TQ CCDI at 156m
1.65
1.55
1.45
1.35
1.25
1.15
1.05
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

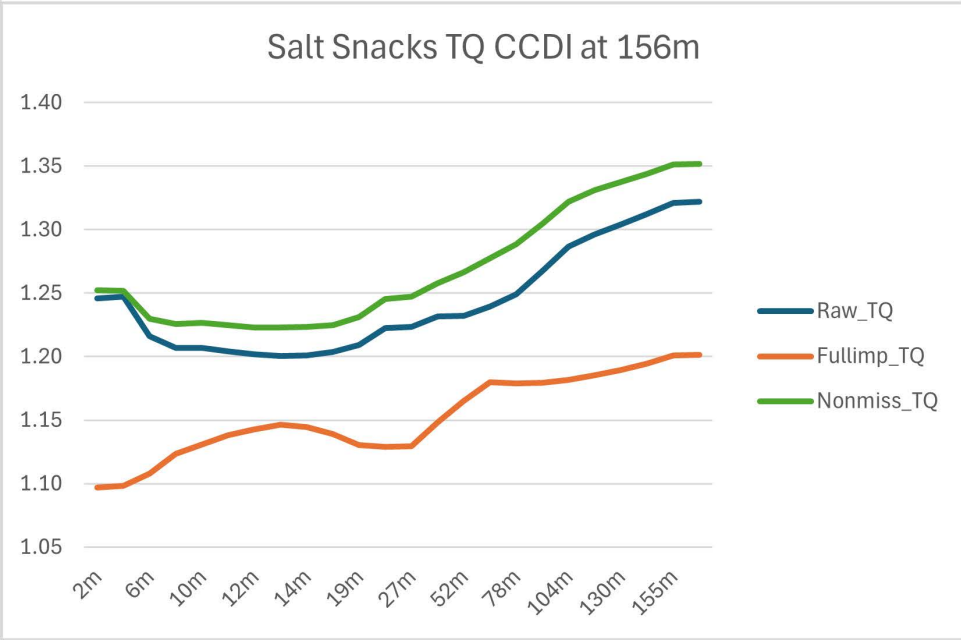

Peanut Butter MPID Test
1.20
1.15
1.10
1.05
1.00
0.95
0.90
0.85
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

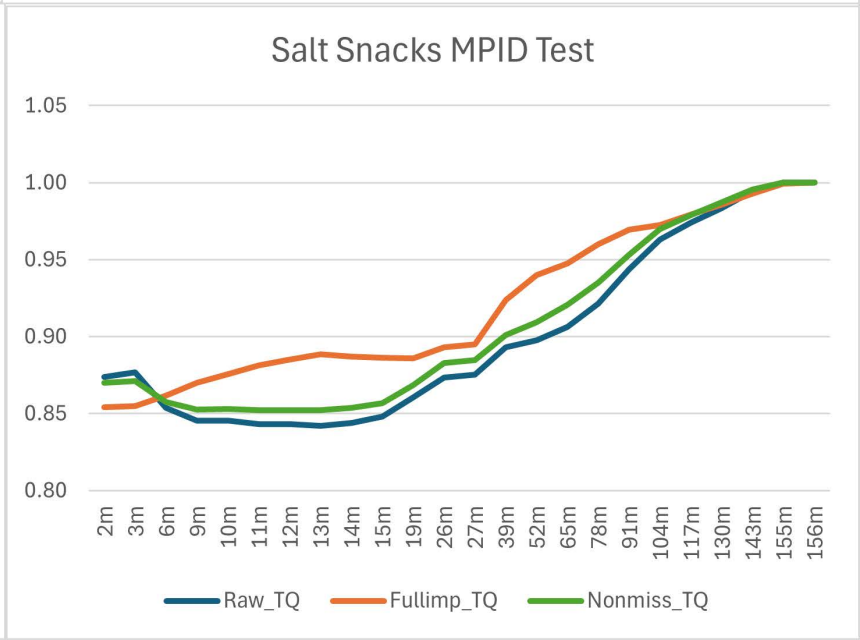

Paper Towel TQ CCDI at 156m
1.40
1.30
1.20
1.10
1.00
0.90
0.80
0.70
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

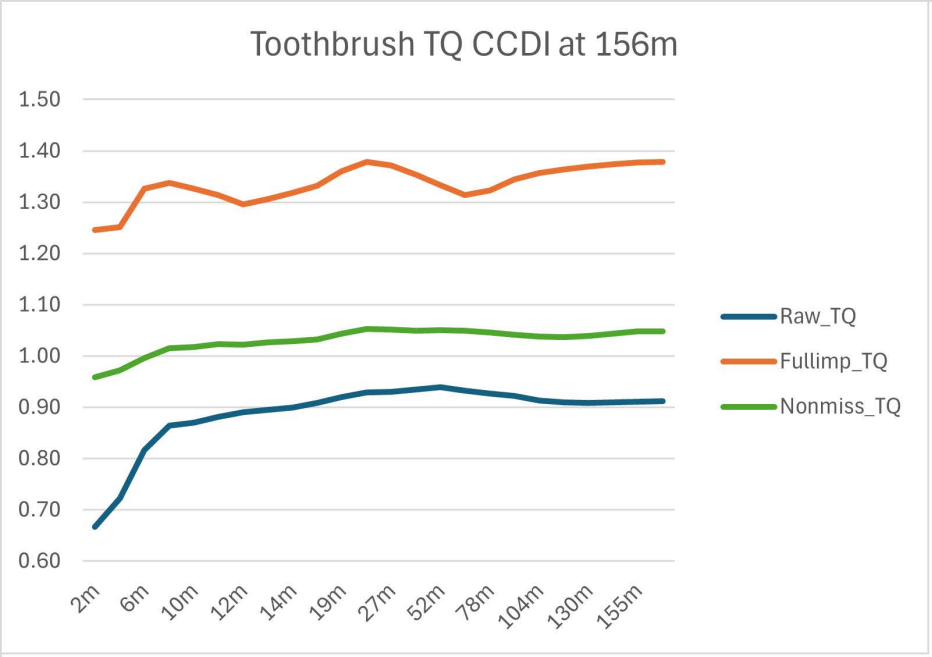

Paper Towel MPID Test
1.10
1.00
0.90
0.80
0.70
0.60
0.50
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

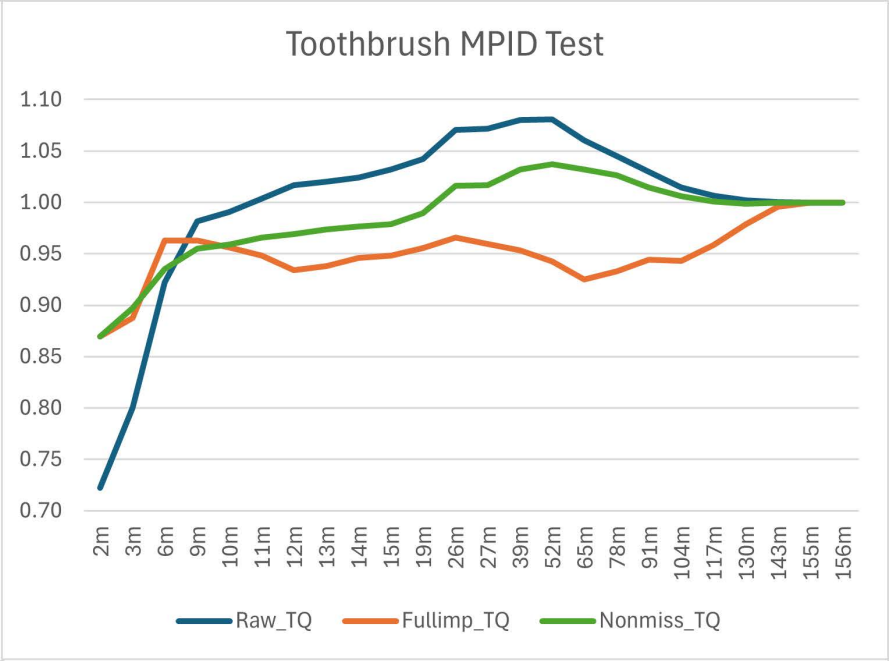

Razors TQ CCDI at 156m
3.00
2.50
2.00
1.50
1.00
0.50
0.00
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

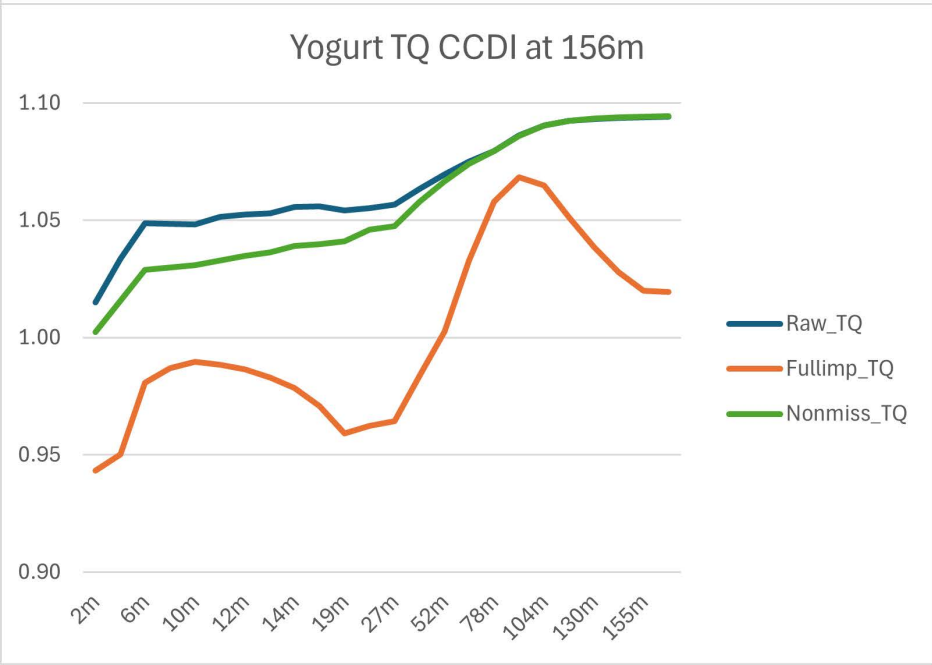

Razors MPID Test
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

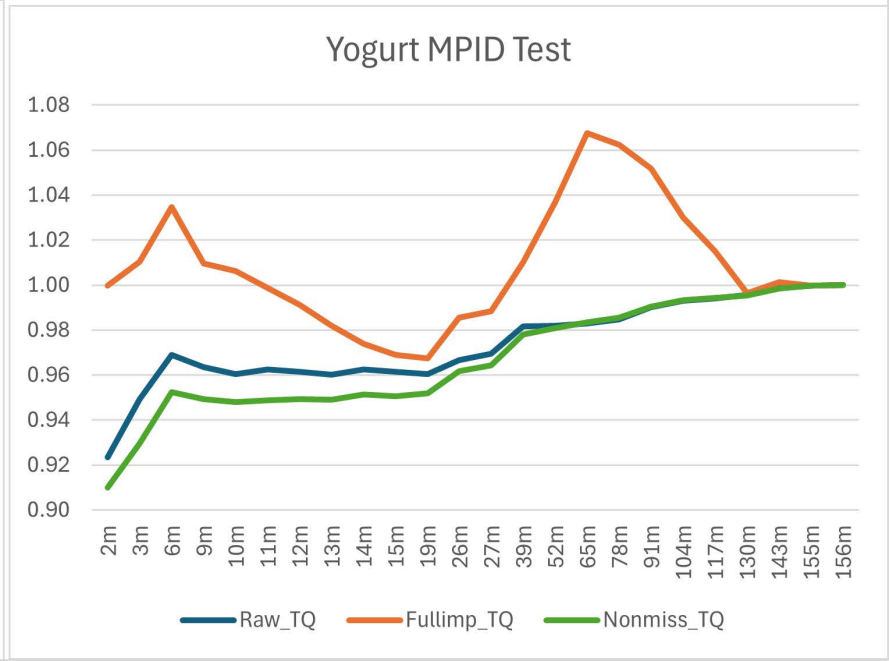

Salt Snacks TQ CCDI at 156m
1.40
1.35
1.30
1.25
1.20
1.15
1.10
1.05
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

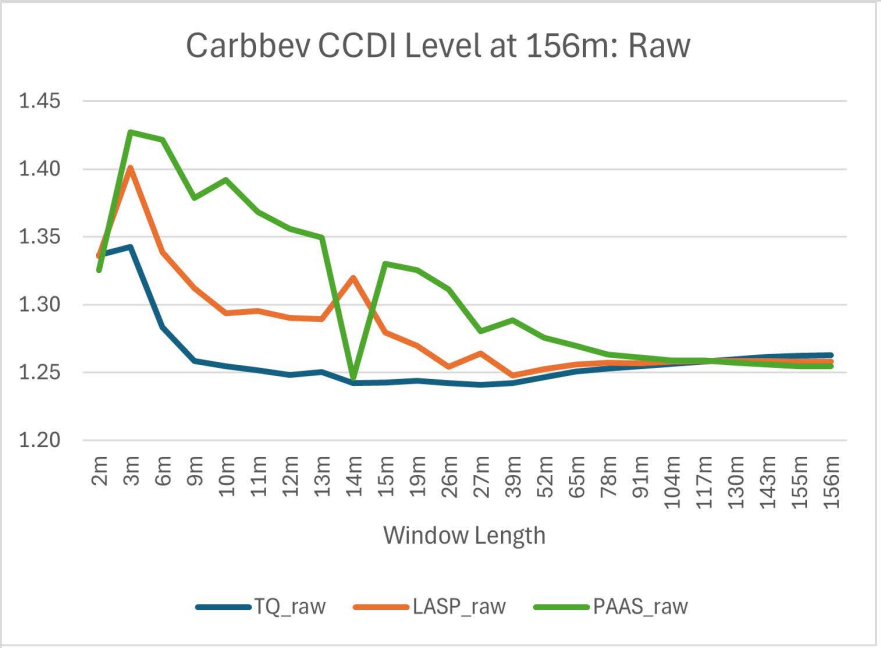

Salt Snacks MPID Test
1.05
1.00
0.95
0.90
0.85
0.80
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

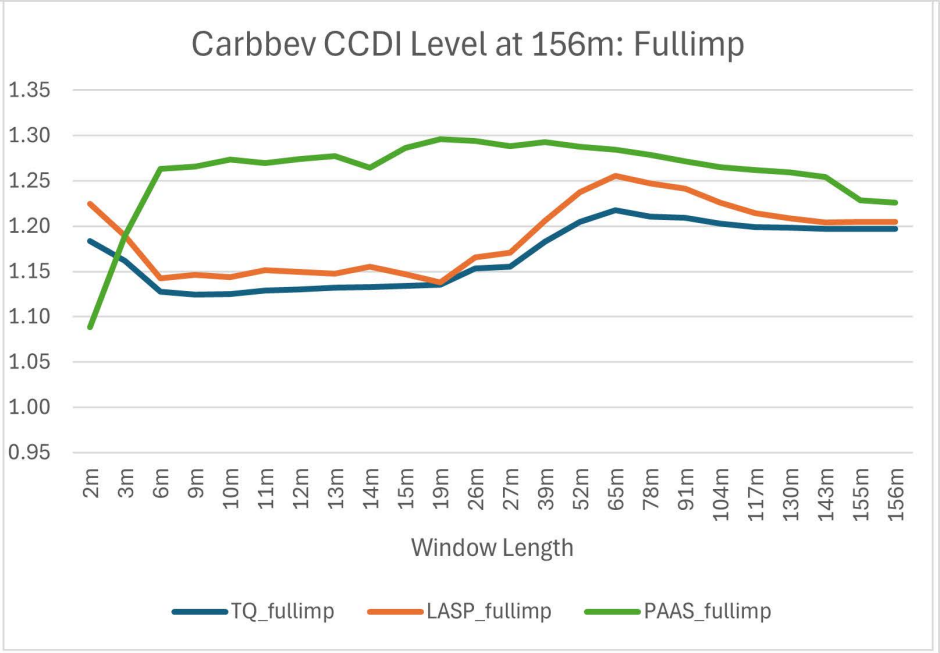

Toothbrush TQ CCDI at 156m
1.50
1.40
1.30
1.20
1.10
1.00
0.90
0.80
0.70
0.60
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

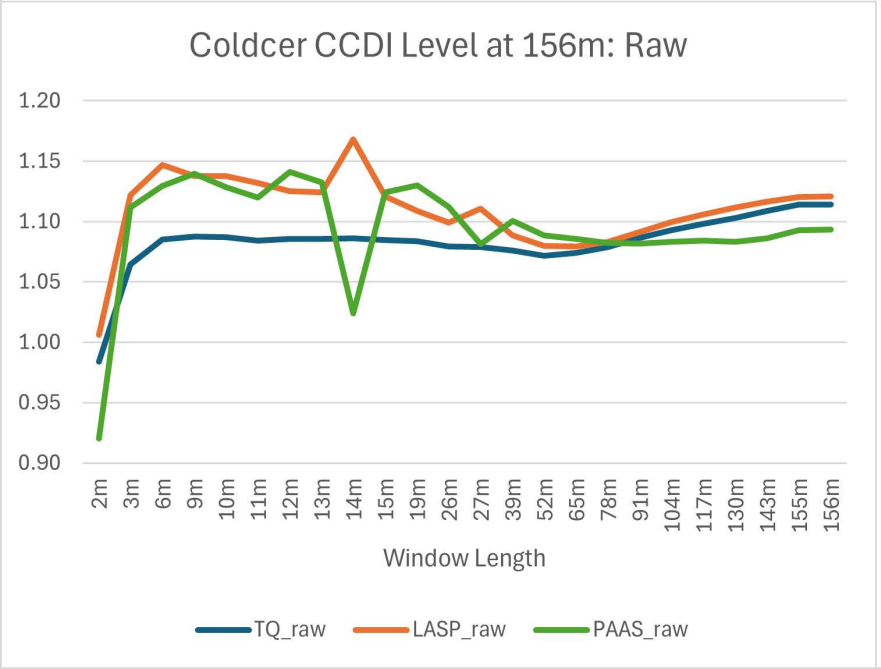

Toothbrush MPID Test
1.10
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

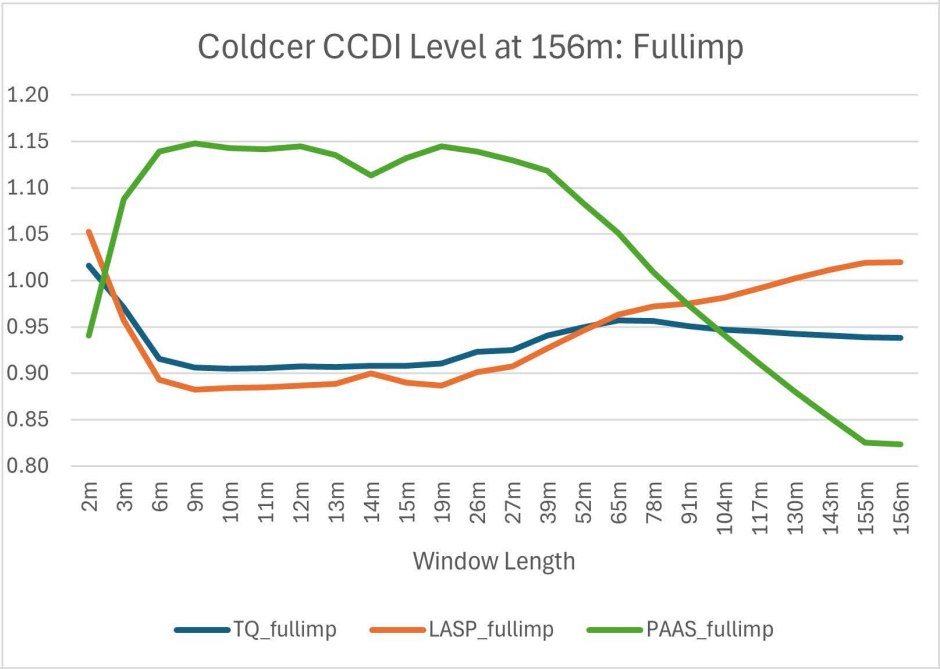

Yogurt TQ CCDI at 156m
1.10
1.05
1.00
0.95
0.90
2m
6m
10m
12m
14m
19m
27m
52m
78m
104m
130m
155m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

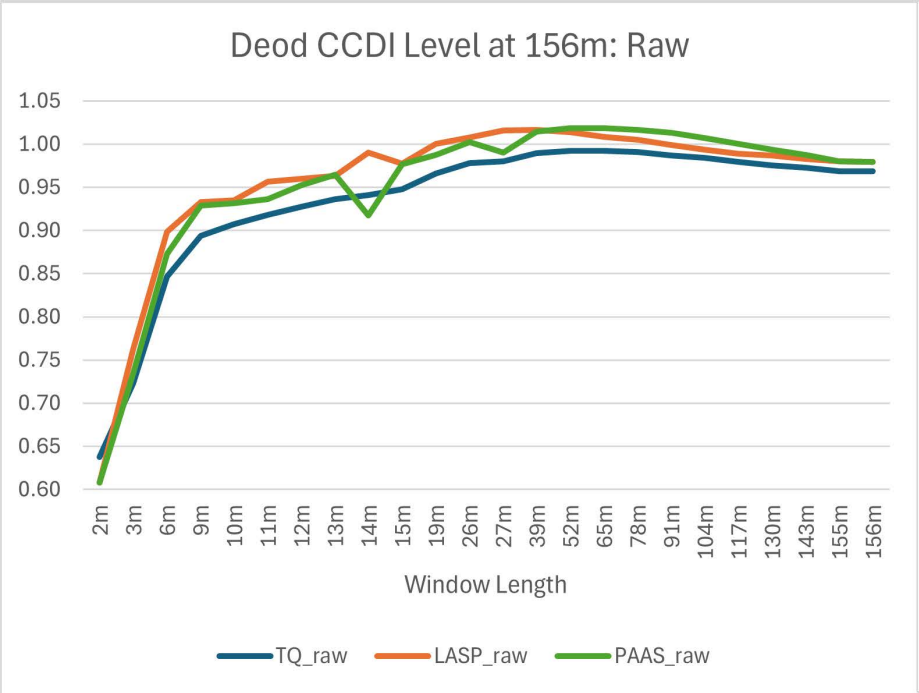

Yogurt MPID Test
1.08
1.06
1.04
1.02
1.00
0.98
0.96
0.94
0.92
0.90
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Raw_TQ
Fullimp_TQ
Nonmiss_TQ

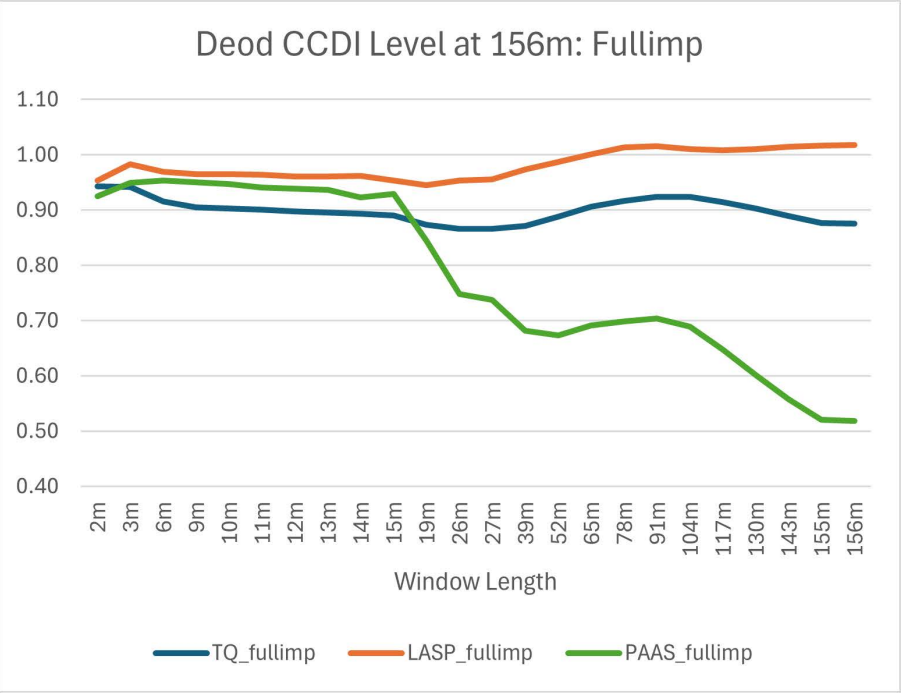

Carbbev CCDI Level at 156m: Raw
1.45
1.40
1.35
1.30
1.25
1.20
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

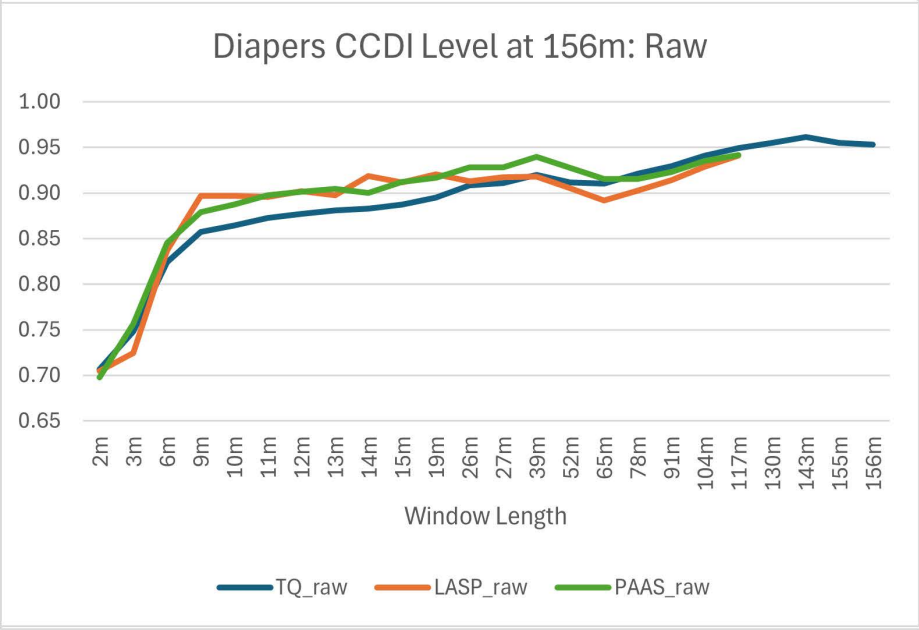

Carbbev CCDI Level at 156m: Fullimp
1.35
1.30
1.25
1.20
1.15
1.10
1.05
1.00
0.95
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

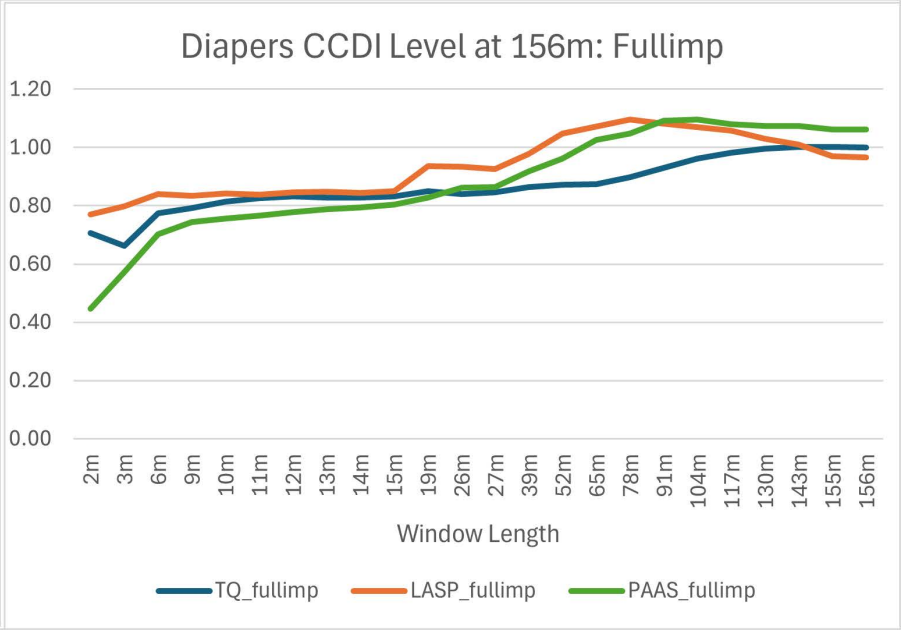

Coldcer CCDI Level at 156m: Raw
1.20
1.15
1.10
1.05
1.00
0.95
0.90
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

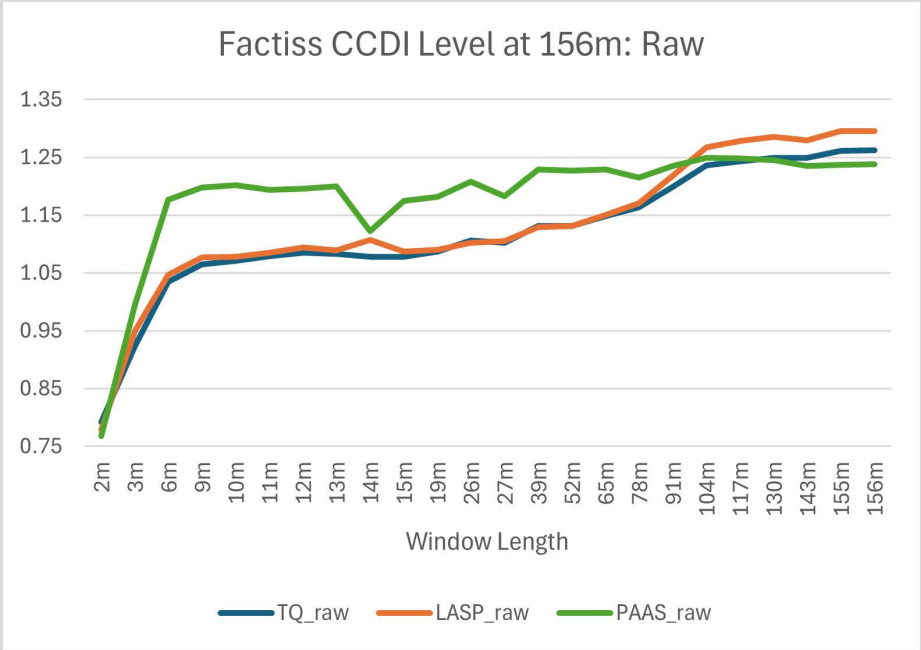

Coldcer CCDI Level at 156m: Fullimp
1.20
1.15
1.10
1.05
1.00
0.95
0.90
0.85
0.80
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

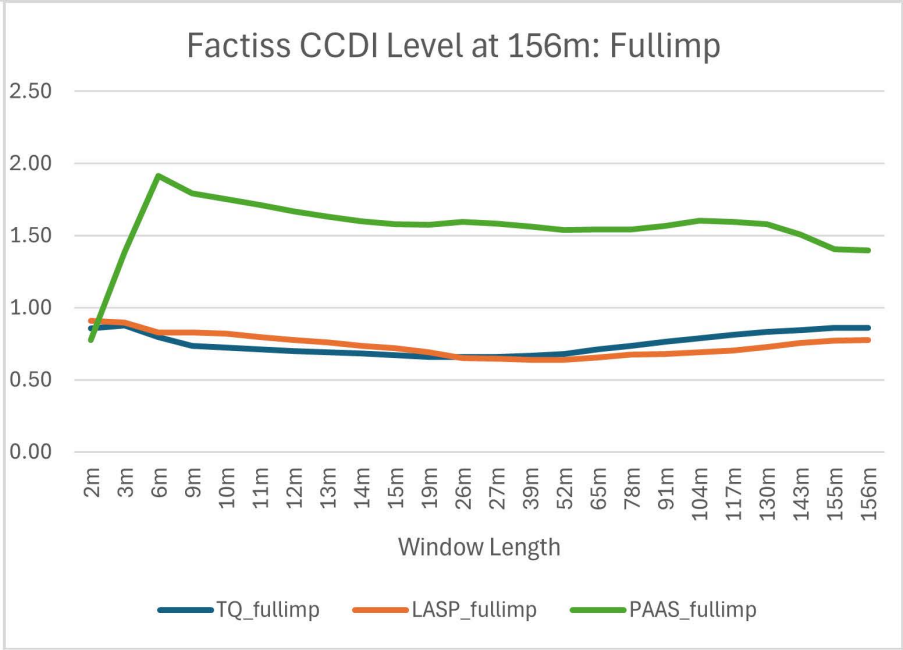

Deod CCDI Level at 156m: Raw
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

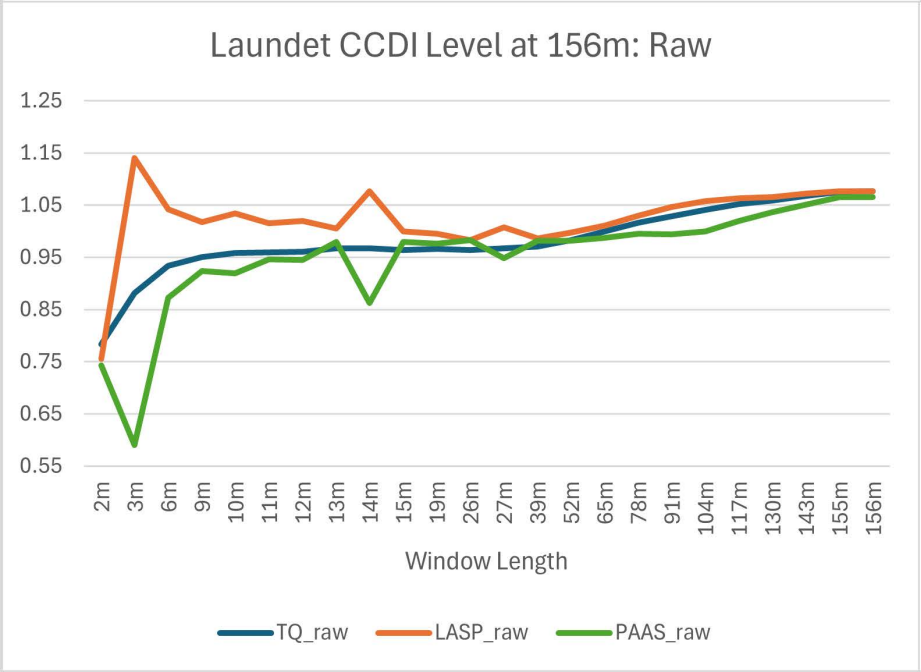

Deod CCDI Level at 156m: Fullimp
1.10
1.00
0.90
0.80
0.70
0.60
0.50
0.40
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

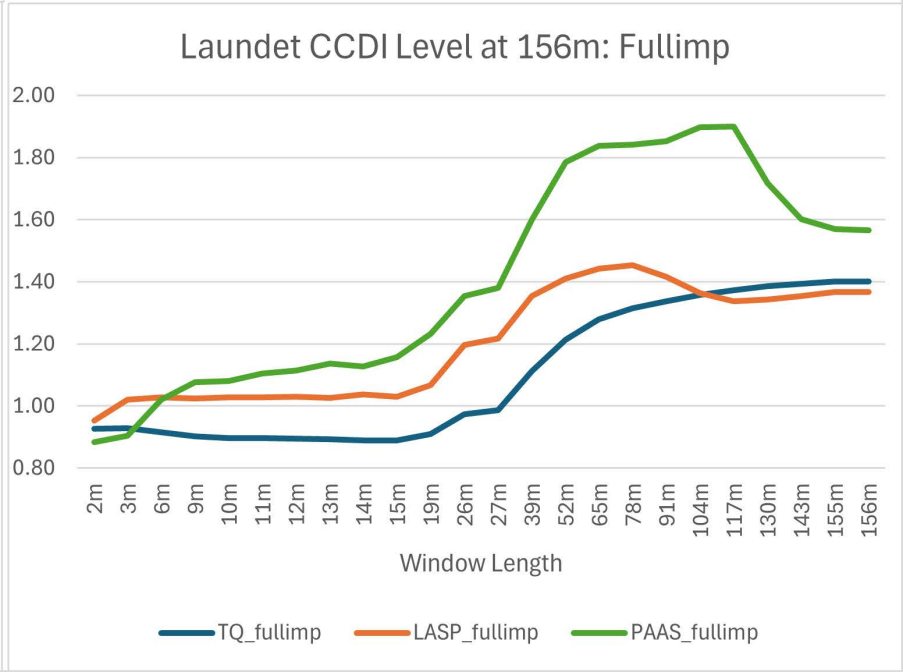

Diapers CCDI Level at 156m: Raw
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

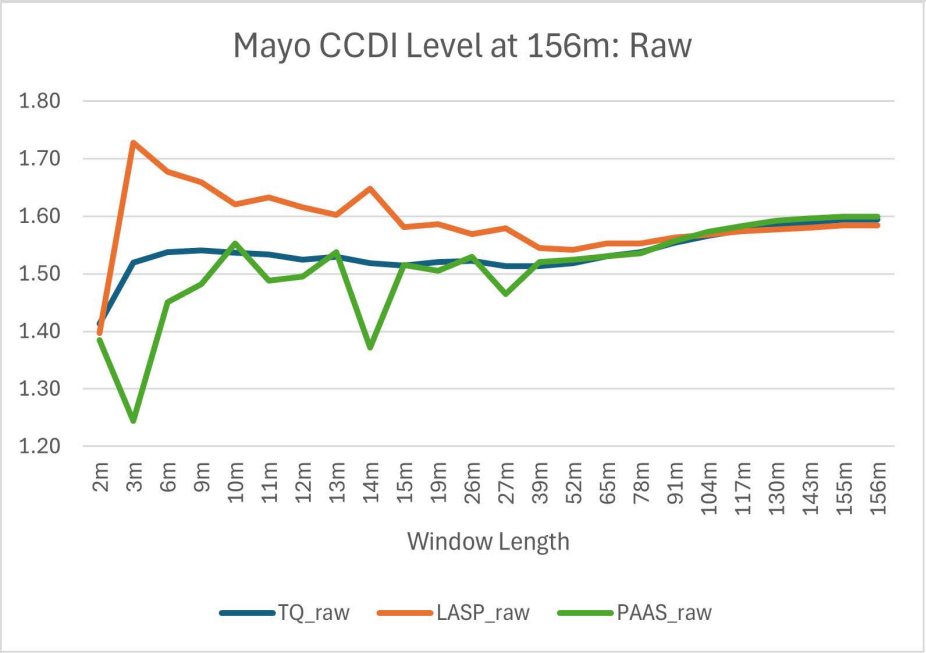

Diapers CCDI Level at 156m: Fullimp
1.20
1.00
0.80
0.60
0.40
0.20
0.00
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

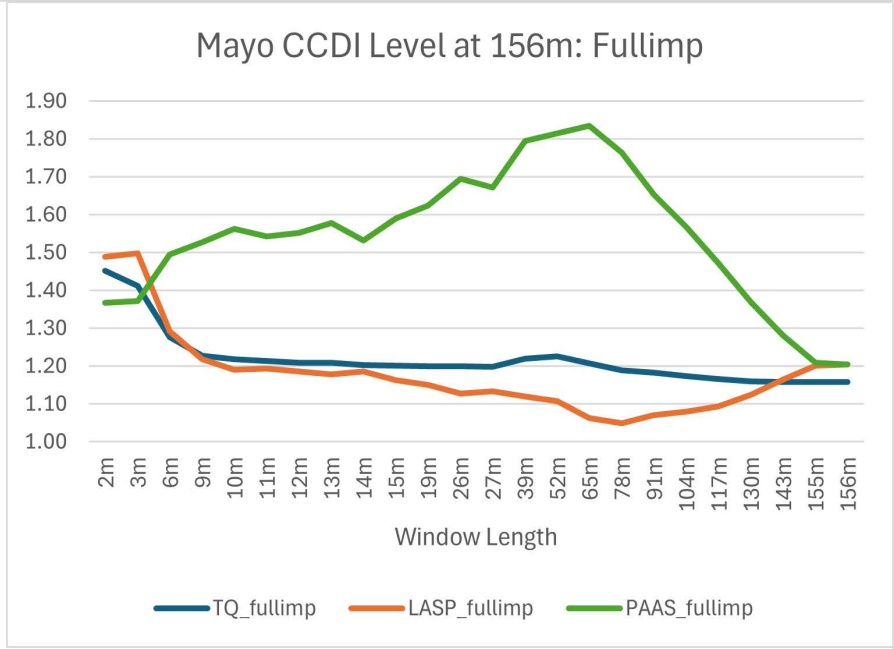

Factiss CCDI Level at 156m: Raw
1.35
1.25
1.15
1.05
0.95
0.85
0.75
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

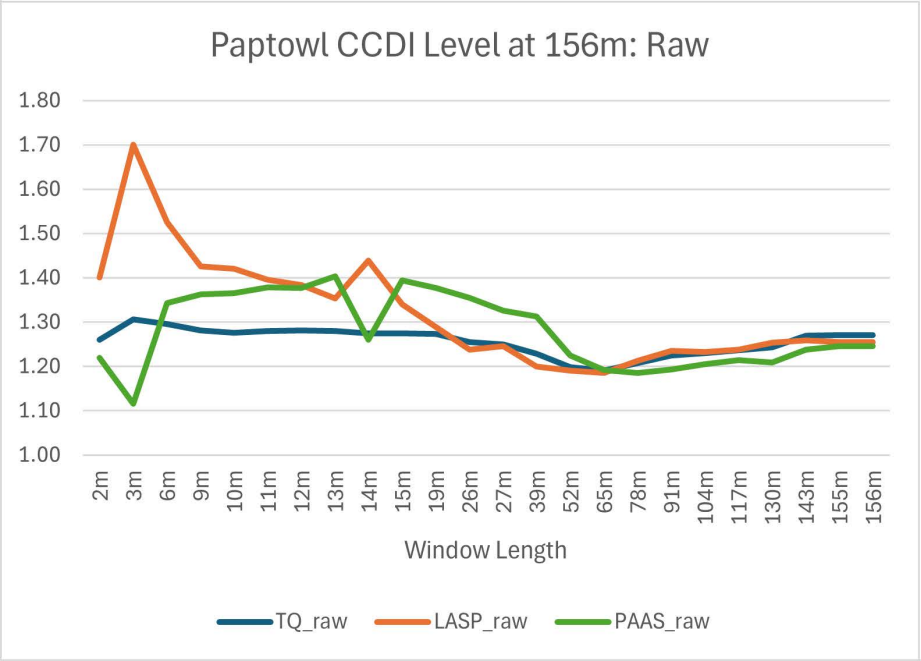

Factiss CCDI Level at 156m: Fullimp
2.50
2.00
1.50
1.00
0.50
0.00
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

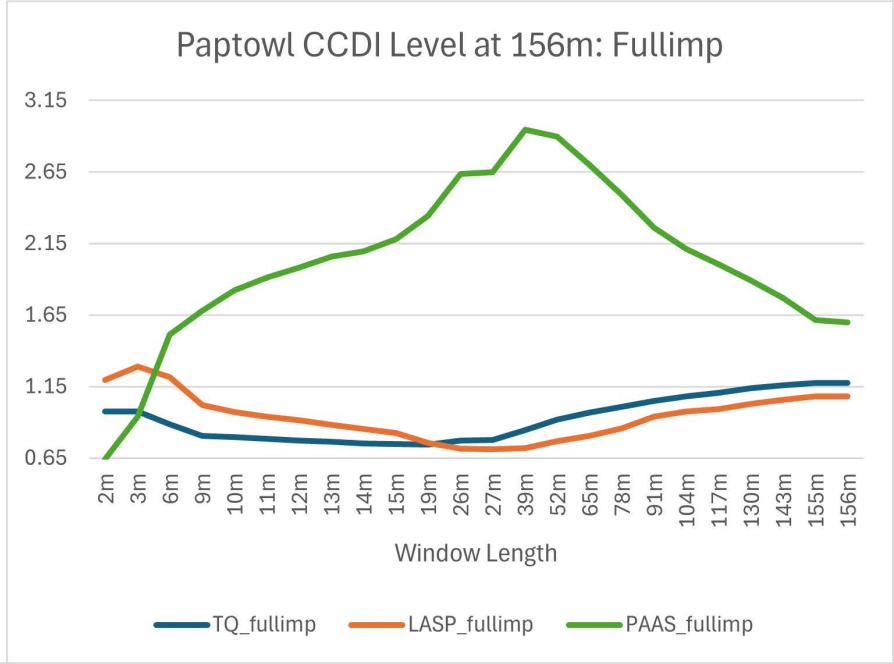

Laundet CCDI Level at 156m: Raw
1.25
1.15
1.05
0.95
0.85
0.75
0.65
0.55
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

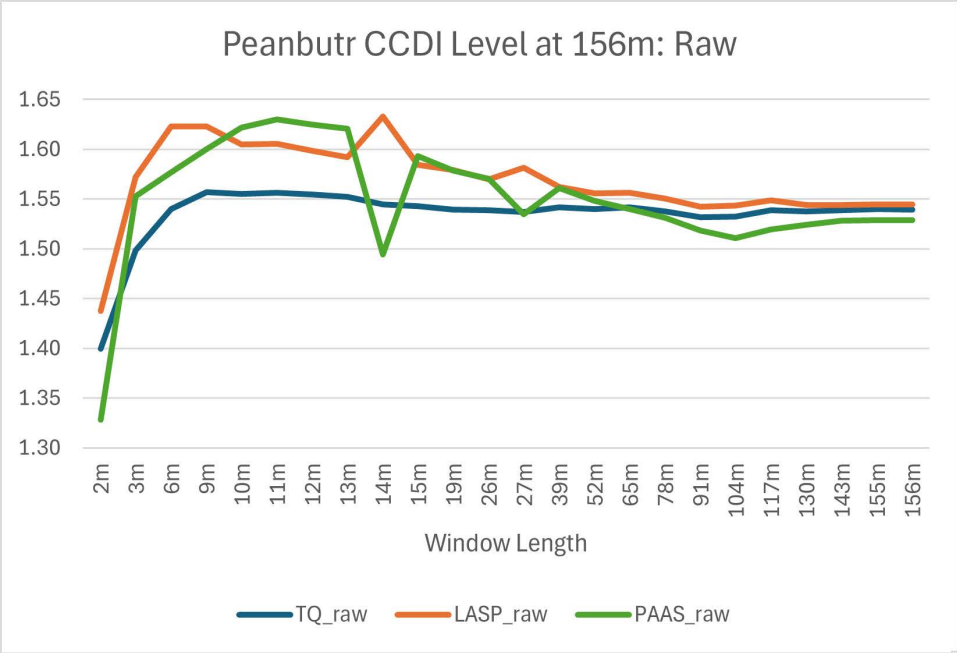

Laundet CCDI Level at 156m: Fullimp
2.00
1.80
1.60
1.40
1.20
1.00
0.80
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

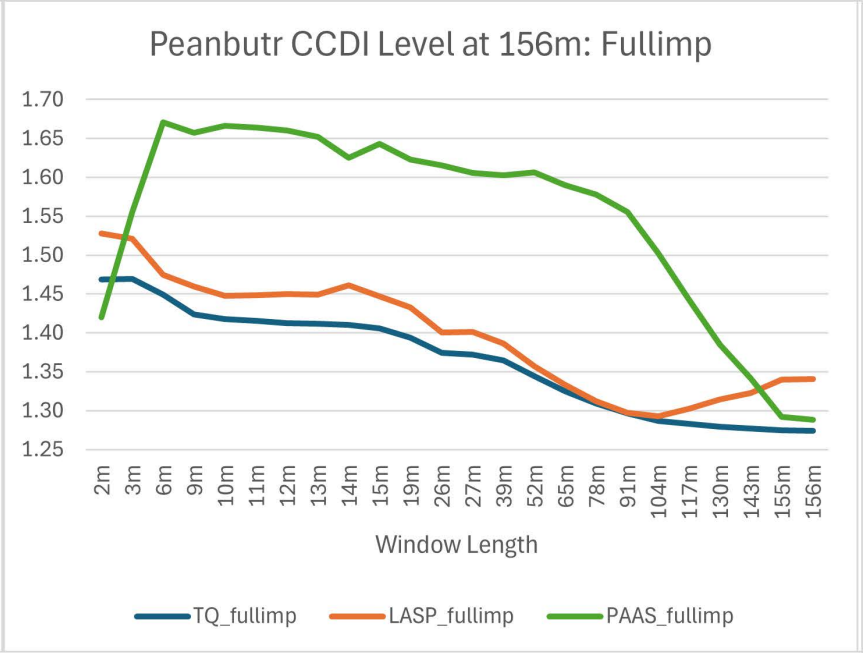

Mayo CCDI Level at 156m: Raw
1.80
1.70
1.60
1.50
1.40
1.30
1.20
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

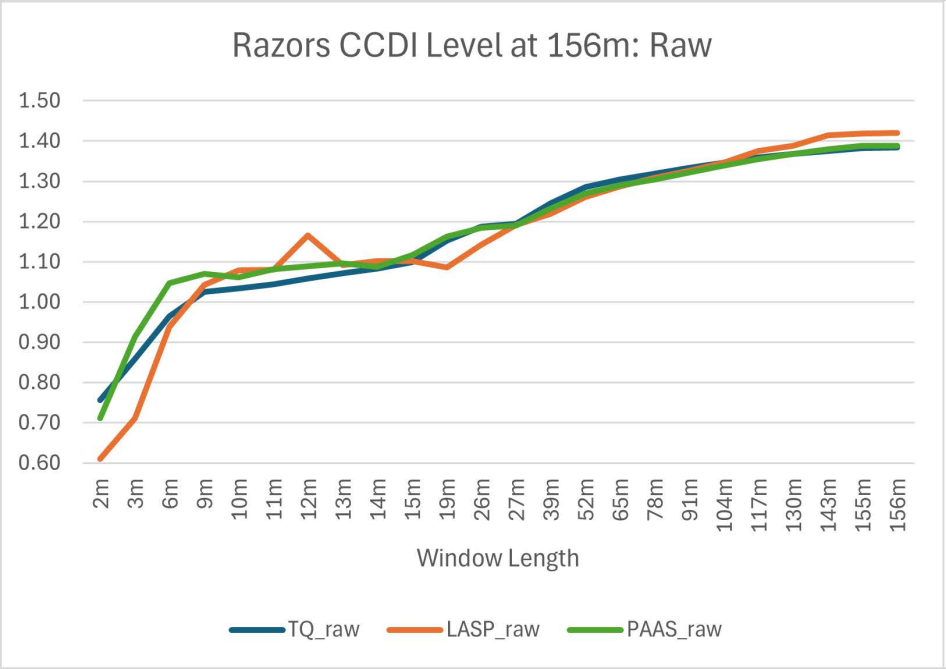

Mayo CCDI Level at 156m: Fullimp
1.90
1.80
1.70
1.60
1.50
1.40
1.30
1.20
1.10
1.00
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

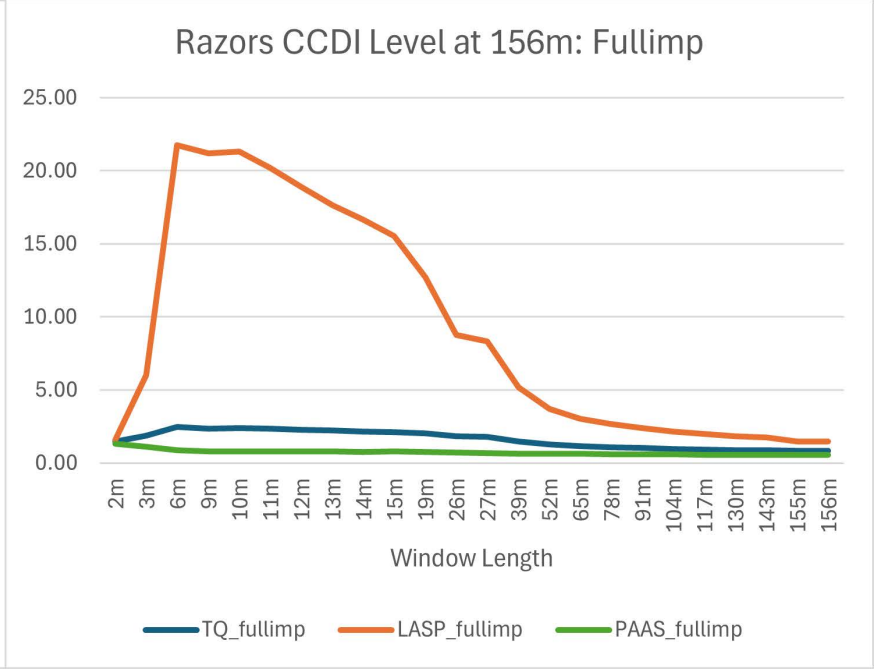

Paptowl CCDI Level at 156m: Raw
1.80
1.70
1.60
1.50
1.40
1.30
1.20
1.10
1.00
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

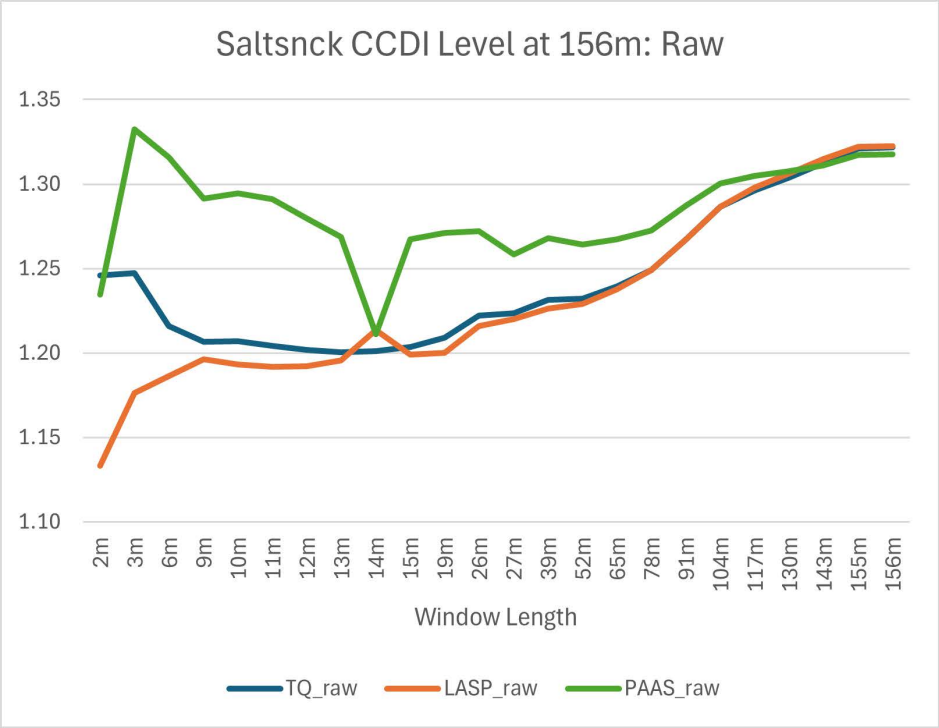

Paptowl CCDI Level at 156m: Fullimp
3.15
2.65
2.15
1.65
1.15
0.65
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

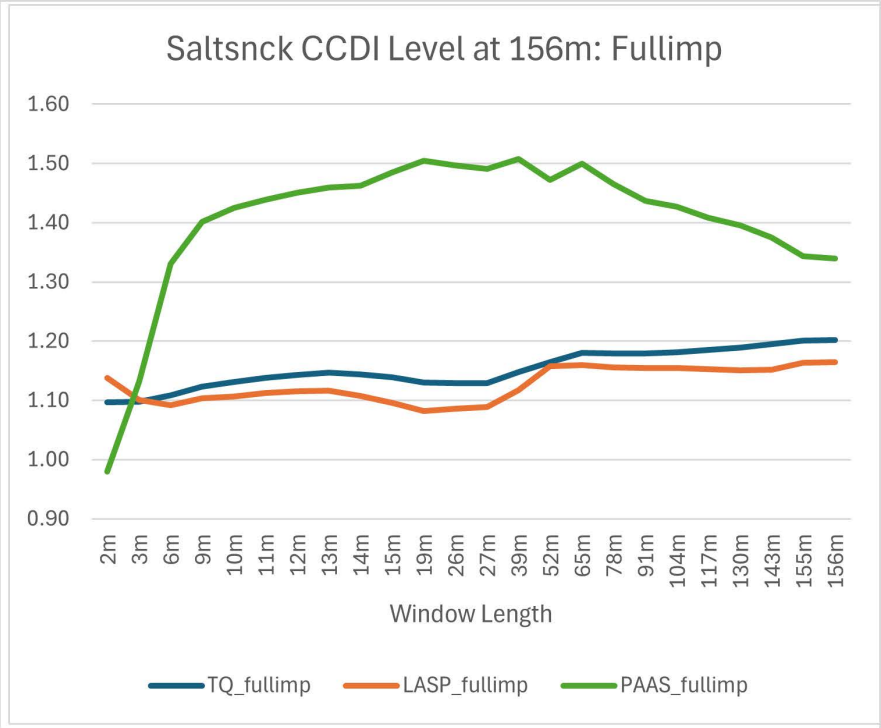

Peanbutr CCDI Level at 156m: Raw
1.65
1.60
1.55
1.50
1.45
1.40
1.35
1.30
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

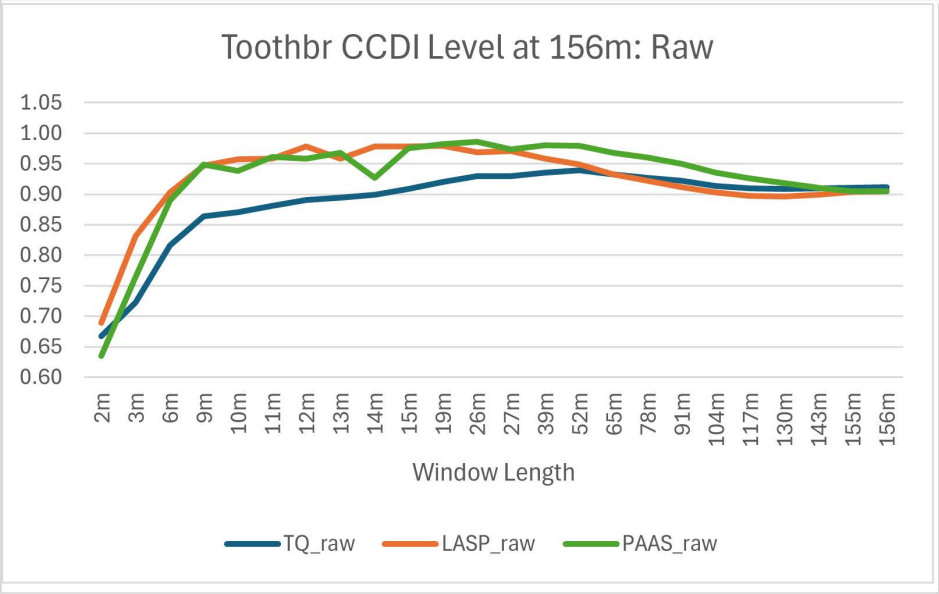

Peanbutr CCDI Level at 156m: Fullimp
1.70
1.65
1.60
1.55
1.50
1.45
1.40
1.35
1.30
1.25
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

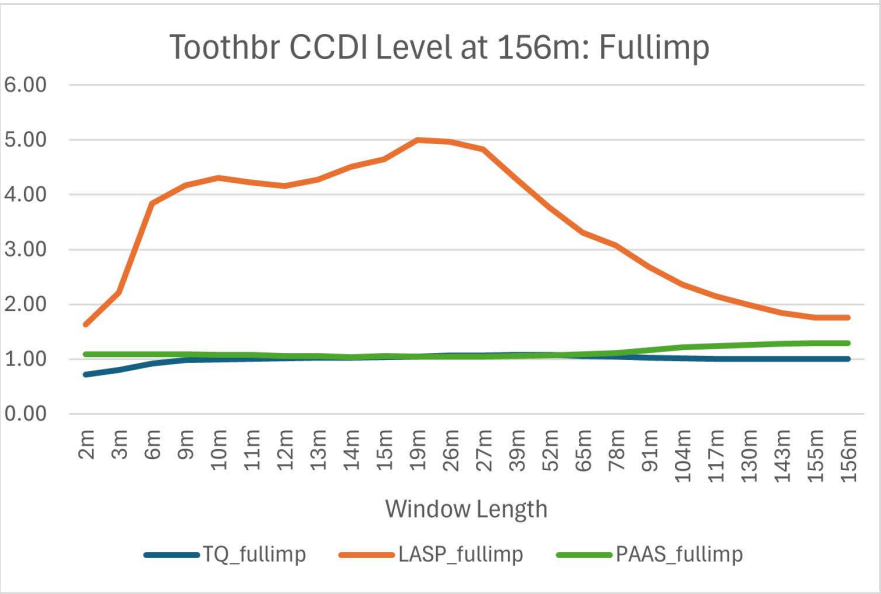

Razors CCDI Level at 156m: Raw
1.50
1.40
1.30
1.20
1.10
1.00
0.90
0.80
0.70
0.60
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw

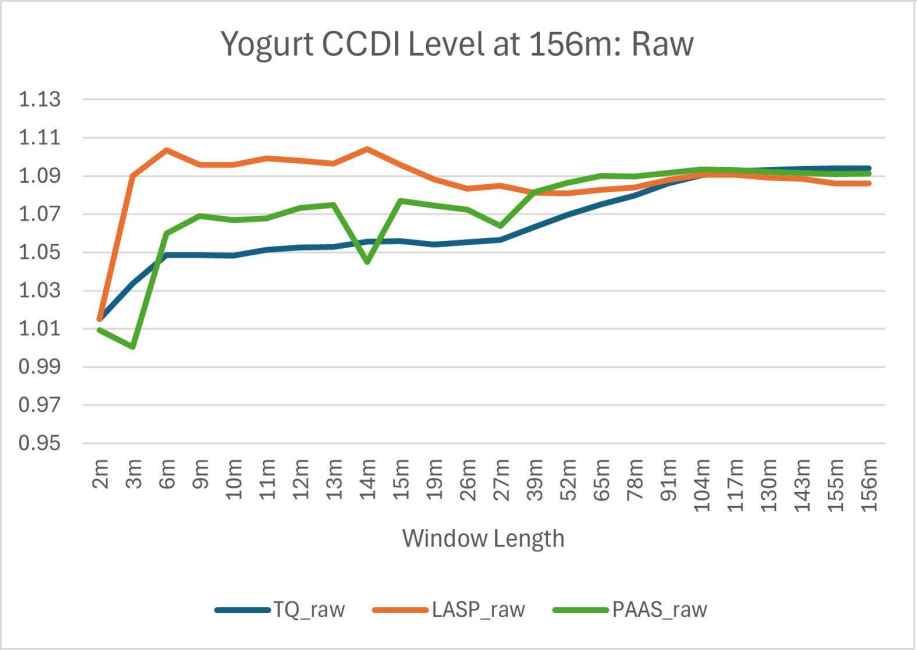

Razors CCDI Level at 156m: Fullimp
25.00
20.00
15.00
10.00
5.00
0.00
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp

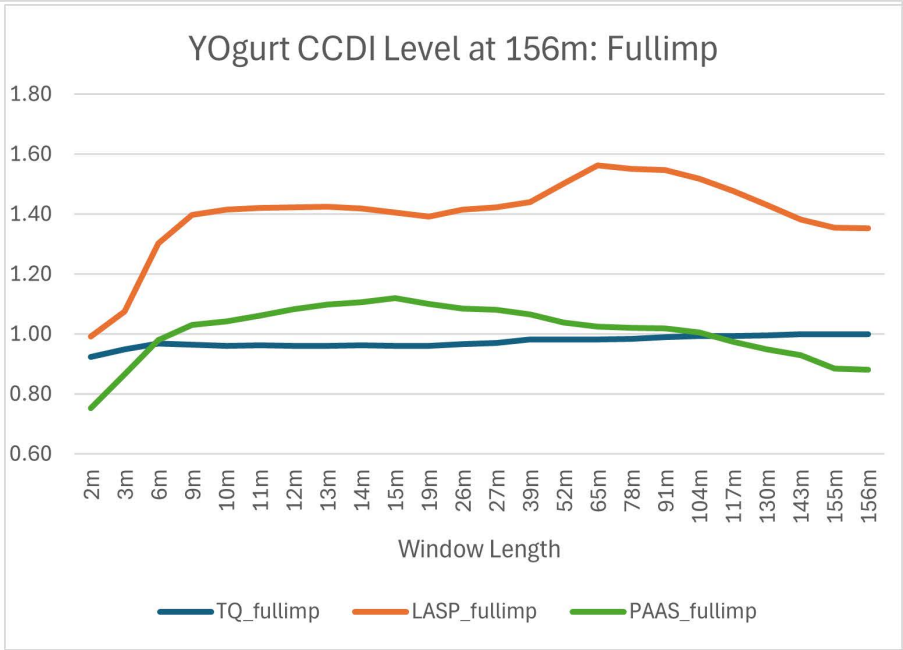

Saltsnck CCDI Level at 156m: Raw
1.35
1.30
1.25
1.20
1.15
1.10
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw


Saltsnck CCDI Level at 156m: Fullimp
1.60
1.50
1.40
1.30
1.20
1.10
1.00
0.90
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp


Toothbr CCDI Level at 156m: Raw
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_raw
LASP_raw
PAAS_raw


Toothbr CCDI Level at 156m: Fullimp
6.00
5.00
4.00
3.00
2.00
1.00
0.00
2m 3m 6m 9m 10m 11m 12m 13m 14m 15m 19m 26m 27m 39m 52m 65m 78m 91m 104m 117m 130m 143m 155m 156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp


Yogurt CCDI Level at 156m: Raw
1.13
1.11
1.09
1.07
1.05
1.03
1.01
0.99
0.97
0.95
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Window Length
TQ_raw
LASP_raw
PAAS_raw


YOgurt CCDI Level at 156m: Fullimp
1.80
1.60
1.40
1.20
1.00
0.80
0.60
2m
3m
6m
9m
10m
11m
12m
13m
14m
15m
19m
26m
27m
39m
52m
65m
78m
91m
104m
117m
130m
143m
155m
156m
Window Length
TQ_fullimp
LASP_fullimp
PAAS_fullimp