

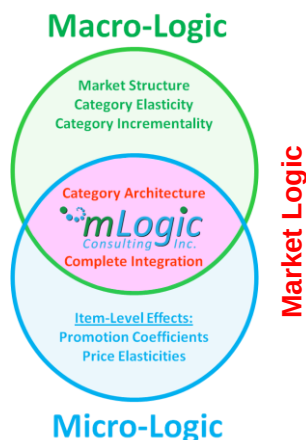
Traditional Modeling Limitations & The mLogic Solution

In an environment where entire categories are facing pricing pressures, COGs are fluctuating and competitive landscapes are shifting, the ability to run broad-based simulations involving all category players is more important than ever. At the same time, retailers are demanding insights to maximize category sales and profits. To fully understand how price, pack size and promotion impact all levels (PPG, brand, manufacturer, category) mLogic has developed a comprehensive approach to modeling to provide the most complete and accurate simulations possible.

mLogic's comprehensive approach combines:

- Bottom-up PPG models ([micro-logic](#))
- Top-down category models ([macro-logic](#))
- A total-market approach ([market-logic](#)).

Thus, our name – [mLogic](#). These components (micro, macro, market) are integrated to create a holistic modeling and simulation system that is more complete, more powerful and more predictive than traditional stand-alone regression approaches.



Forest for the trees

Similar to typical regression modeling approaches, mLogic's [micro-logic component](#) consists of multiple regression models run for each PPG using granular POS scanning data (weekly retailer data covering the majority of the country). Models are set up to include variables for regular price, pack-size, promoted discount, promotion types, promotion frequency, distribution and seasonality. mLogic models all key PPGs for near complete category coverage.

If we stopped there, the mLogic approach would be very comparable to traditional modeling approaches. But the traditional multiple regression approach has several inherent shortcomings, especially when applied to entire categories. These “blind spots” are inherent in the typical approach and become very significant when PPG models are aggregated to levels such as Brand, Manufacturer or Category. **Why is this?**

[Problem #1 – missing competitive cross-effects.](#)

Standard regression models were originally designed to help marketers understand how a few of their own pack-sizes react to changes in their own prices and promotions and how they interact with a few key competitors. But due to multicollinearity and over-specification limitations, the standard regression model is capable of modeling cross-effects for only a few key competitive packs – typically large-share PPGs as chosen by the modeler. This is a significant problem when modeling a category with 100+ PPGs! *This approach assumes zero cross-effects with all of the other packs in the category.* As a result, each PPG model under-states competitive cross-effects *and therefore over-states category effects.* Which leads us to...

Problem #2 – no category perspective. PPG models that are set up and run in isolation don't have a category perspective. How could they? By definition, each PPG model set up in the traditional manner with a very limited set of competitive packs will have a very limited view of what the impact of price and promotion actions will have on category sales. In a sense, the PPG models can't see the forest for the trees. Take a simple example – The Diapers category:

What if the price of all diapers rose simultaneously by 10% (perhaps driven by category-wide COGs pressures)? What would happen to the total number of diapers sold at the national level? We know intuitively that the answer is “not very much!”. Babies don't care about the price of diapers; parents aren't going to double up or switch to cloth and they certainly aren't going to go without! We know intuitively (and this is verified with category-level modeling) that the Diapers category as a whole has a price elasticity close to zero at the national level. To be truly accurate, a rollout of Diaper PPG models should predict a very small category impact.

But they don't. Traditional PPG models, set up in isolation from each other and with limited competitive cross-effects will predict a significant reduction in total diapers sold – clearly a wrong answer. And if the PPG models are wrong in aggregate, they must be wrong individually.

Key point – a system with complete competitive cross-elasticities that tie out to category elasticity would be much more powerful and predictive! mLogic's [macro-logic component](#) integrates complete PPG cross-effects into a category elasticity so that roll-ups tie out at all levels of the category.

Problem #3: managing price through pack size.

Perhaps the most common method of increasing price is by reducing package size. Manufacturers learned long ago that reducing weight or count is much easier than taking price points up. Actual price point increases are more noticeable to the consumer, are more likely to alienate retailers and have additional complications such as ripple effects to the promotional plan, crossing price thresholds, etc.

Any comprehensive modeling and simulation solution must include the ability to simulate pack-size changes to understand the impact on sales and profits. mLogic has developed this capability as part of our overall modeling approach.

Problem #4: What about cross-retailer switching?

Traditional regression modeling approaches are incapable of *directly* measuring the degree to which price or promotion actions in one store impact sales in another store. This capability is not offered in the standard PnP modeling services offered by Nielsen, IRI, mLogic or other vendors.

However, mLogic's [market-logic component](#) implicitly accounts for this effect through a hierarchical approach to elasticities and promotion incrementality. For instance, a promotion run in a Food retailer will drive more incremental units in that retailer than in the Food channel as a whole due to cross-market cannibalization. And price elasticity will be greater at the retailer level than at the channel level or at the Total country level. While we aren't directly measuring the cross-market source of cannibalization we implicitly account for it through this approach.

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