“Where in the World Is the Market? The Income Distribution Approach to Understanding Consumer Demand in Emerging Countries”

AUTHORS	Staffan Canback Frank D'Agnese
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Staffan Canback (USA), Frank D'Agnese (USA)

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Abstract

Finding, measuring and capturing market opportunities in emerging countries are critical tasks for multinational consumer goods companies. Central to these tasks is the need to collect and analyze income distribution data within a globally coherent framework and to move beyond income metrics based on national averages.

This article describes a new framework and dataset that achieves this goal and demonstrates how income distribution data, combined with consumer and marketing data, can be incorporated into simple demand models such as the Bass diffusion model or the Golder-Tellis affordability model to understand market dynamics. Our analytical effort is the first example of income distribution data being used to assess market opportunities in emerging countries.

We find that demand models based on the number of people within various income brackets at national or local levels are superior to models based on average income. We further find that combining income distribution data with pricing, marketing spending, consumer behavior and distribution coverage data makes it possible to measure which factors drive demand at the brand level — even in hard-to-analyze countries.

Keywords: consumer goods, global income distribution, marketing, predictive analytics.
JEL Classification: M20.

Introduction

The objective of the article is to introduce a new and original way to analyze demand for consumer goods based on income distribution. It contributes to marketing science in three ways. First, it is a pioneering attempt at building demand models based on how many individuals or households there are within different income brackets rather than to use average incomes. Second, it introduces a unique global dataset that for the first time describes how income is distributed in the world, down to the city level. Third, it applies models and data to consumers in emerging countries and demonstrates that accurate predictions can be made even in hard-to-analyze countries. To achieve this, we bridge scientific domains by introducing knowledge developed in prosperity and poverty research into marketing research.

Conceptually, we claim there are three hierarchical levels of market sizing models for emerging countries and the choice of model depends on the data available (Fig. 1). The first level is to size and forecast demand using income distribution data only. Our research shows that this is a valid model when estimating category demand. The second level consists of models that combine income distribution data with other variables (such as marketing spending or consumer sentiment) at the aggregate level. The third level contains models that use a combination of aggregate (macro) data and individual (micro) data. Each level is a direct extension of the level above it.

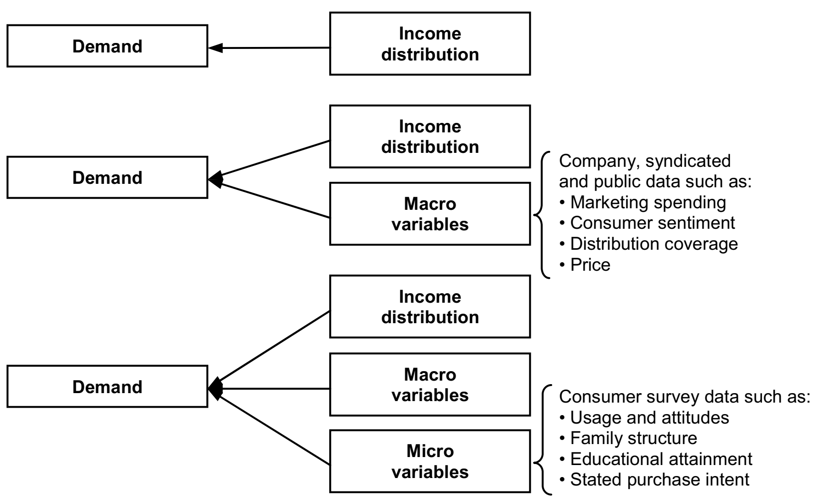


Fig. 1. Hierarchical levels of predictive models for emerging countries

Consumer markets are increasingly geographically dispersed. While world output has grown at 3% per year since 1990, emerging countries have grown at almost 5% (Maddison, 2001; World Bank, 2008). As a consequence, more than 60% of incremental world output between 1990 and 2008 came from emerging countries, creating vast new markets for branded consumer goods companies.

For large companies, this presents both opportunities and challenges. A quarter-century ago a company could view itself as global if it was active in a handful of affluent countries such as the G7. Today, it has to consider marketing its products or services in 35 to 40 countries with a total population of five billion people. At the same time, profitability is typically lower for geographically diversified companies (Canback, Samouel and Price, 2006).

Making global strategic choices that optimally marshal a company's resources is therefore increasingly important. No one company can serve five billion people in a meaningful way, nor are all of these people potential customers. Yet few companies can say with confidence whether their potential market in Latin America is larger than in China, or whether São Paulo holds more potential than Shanghai.

To answer such questions, the single most important fact required on the demand side is how many people in a given geography can afford the product or service (Lambert and Pfähler, 1997). The importance of income distribution data in predicting demand in emerging countries stems from four interacting sources. First, there is a large subset of the population that does not have the means to buy a product or service no matter how much they yearn for it. This is in sharp contrast to people in affluent countries who mostly can afford to buy any product as long as they are willing to make trade-offs. Second, higher income consumers tend to understand marketing messages because of higher educational attainment. Third, availability of branded consumer goods is closely related to the development of modern trade. And the size of modern retail trade is almost perfectly correlated with the number of people above a certain income level[1]. Fourth, higher income households are more concentrated to cities in emerging countries than in affluent ones. Combined, this means that knowing the actual number of people at a given income level at the local (city) level is more important than in affluent countries.

The remainder of this article discusses the first income-distribution-based framework and how it can be used to assess market potential locally all over the world and to build marketing programs. We describe a global income distribution database which contains information on how many people are in a certain income bracket in each city, other urban areas and rural areas around the world. We demonstrate that for most products and services, income is an important driver of demand and we show three applications from strategy development and marketing where we combine the income distribution with other demand drivers such as price, product/service benefits, consumer sentiment, retail presence and marketing spending.

1. Literature review

Predicting demand for products and services is a critical task for most companies. Dalrymple (1987) found that 99% of US companies surveyed included predictions in their strategy and marketing plans and that they were critical to the companies' success. As a corollary, the literature on demand analysis is extensive. In this section, we focus on the subset of the literature that deals with income-based econometric models for predicting markets outside affluent countries. We find that there are few such articles and only one, to our knowledge, uses income distribution. This is in line with the finding of Talukdar et al. (2002) who note that "existing studies tend to limit their analysis to industrialized countries".

1.1. Predictive models. Accurate predictions do not necessarily stem from complex analytical techniques. Armstrong and Brodie (1997) argue that 1) methods should be simple because "complex methods have not proven to be more accurate than relatively simple methods" and 2) methods "should be developed primarily on the basis of theory, not data".

Among quantitative predictive techniques, strategy and marketing professionals often use diffusion or affordability models combined with consumer research to predict market responses to product introductions, price changes, advertising and promotion efforts, expanded distribution coverage and other managerial actions. These models meet the criteria of being simple and based on theory.

The Bass model is the best known diffusion model. The model predicts period demand from new buyers based on how many people bought the product in previous periods and how well information about the product spreads among consumers (Bass, 1969). Over the past 40 years, the model has been repeatedly validated and has been improved in numerous ways.

Horsky (1990) extended the model to take into account price and income distribution (Fig. 2). The Bass-Horsky model shows that the diffusion mechanism typically is weaker than the original Bass model suggested and that price/income effects are substantial.

[1] Not discussed further in this article. For evidence, see Traill (2006).

$$S_t = \frac{\theta \cdot M_t}{1 + e^{-\left[i_t - k\bar{p}_t\right]/\delta_t}} - Q_{t-1}$$

S – sales;
θ – proportion of potential buyers;
M – number of households;
i – income;
δ – income dispersion coefficient;
p – price;
k – utility coefficient;
Q – number of previous buyers.

Fig. 2. Bass-Horsky model

Golder and Tellis (1998) suggested an affordability model as a simpler and more accurate alternative to diffusion models. The model explicitly takes into account price, income, consumer sentiment, market presence (i.e., distribution coverage of the product) and marketing drivers (Fig. 3). The model is expressed in the multiplicative Cobb-Douglas form which typically fits data well, allows for easy conversion to a linear regression format by taking the logarithm of variables, and generates results in the form of elasticities.

$$S_t = P_t^{\beta_1} \cdot I_t^{\beta_2} \cdot CS_t^{\beta_3} \cdot MS_t^{\beta_4} \cdot M_t^{\beta_5} \cdot e^{\varepsilon}$$

S – sales;
P – price;
I – income;
CS – consumer sentiment;
MP – market presence (distribution coverage);
M – marketing spending.

Fig. 3. Golder-Tellis model

An added benefit of affordability models is that they are particularly useful in developing economies. In such countries, a significant share of the population cannot afford a good even if they want to buy it. This implies that nondurables can be analyzed using the model. Further, retail availability is explicit in the model. This enhances the predictive power of the model because lack of distribution is often a bottleneck in less affluent countries.

The common themes for these models are that they are simple to use, they are based on theory and that availability of income distribution data is crucial. However, neither model has been extensively tested outside affluent countries.

1.2. Market sizing in emerging countries. Our literature review reveals only a few articles that discuss quantitative market sizing and assessment in emerging countries. To illustrate, among the 106 articles published in the *International Journal of Marketing* between 2002 and 2007, one dealt materially with market sizing in those countries. Similarly, one of 158 articles over the same period in the *International Journal of Forecasting* dealt with topics related to our research.

Copulsky (1959) is perhaps the earliest authority discussing consumer modeling in emerging countries. He notes that demand modeling in many such countries is particularly difficult because of rapid economic development and a lack of reliable data. Armstrong (1970) discusses an econometric modeling approach using the ability to buy (living standard), potential market size and consumer needs as independent variables.

The most relevant article to the current research is Talukdar et al. (2002). Their research explicitly tests a variant of the Bass-Horsky model and incorporates distribution coverage from the Golder-Tellis model. The analysis takes income distribution into account by using the Gini index as an indicator. The dataset includes data for 6 consumer durables covering 10 emerging and 21 affluent countries with the analysis performed at the national level. Their model shows good fit and most of their variables are statistically significant. They note the importance of the Gini index when estimating demand for consumer products.

1.3. Income distribution. The study of income distributions is a relatively new research topic. A review of the field's literature (Heshmati, 2006) lists no important articles written before 1996. It notes that "in the 1990s there was a shift in research…to one focused on the analysis of the distribution of income…This shift is among other things a reflection of the changes in technology". In fact, neither methods nor data existed before the mid-1990s to reliably analyze income distribution effects on a global basis.

Over the past decade, this picture has changed dramatically. A significant volume of research has been published, though most studies deal with prosperity and poverty issues in economics. Income distribution analysis has yet to find its way into strategic or marketing analysis. However, the methods developed in economics research are applicable to the analysis of business issues. An example is Voitchovsky's analysis demonstrating that the shape of the income distribution has a significant impact on demand (Voitchovsky, 2003).

From a data perspective, the ideal situation would be if the income of each individual on this planet was available over time and in a comparable metric across countries. Clearly, this is not feasible. Instead, there are at least four methods to estimate income distributions (Heshmati, 2006):

- aggregating actual national survey data on income and expenditure at the individual level by quintile or decile and assuming uniform income within each income bracket (Milanovic, 2002);

- using the national mean income augmented by a measure of dispersion such as the Gini coefficient (Quah, 1999; Sala-i-Martin, 2002; Schultz, 1998);
- applying known income distributions from benchmark countries to other countries (Bourguignon and Morrisson, 2002);
- combining micro (income survey) and macro (national accounts) data to create continuous income distribution curves (Dikhanov and Ward, 2001).

Among these methods, Dikhanov and Ward's method is the most interesting from a business perspective because it estimates the actual income distribution with high precision; it allows for analysis between and within countries; it expresses results in number of individuals or households; and it is aggregative.

An important consideration when comparing income between countries is what exchange rate to use. The purchasing power parity (PPP) method has evolved as the dominant one for making such comparisons and is today broadly accepted as the basis for any serious analysis[1]. PPP rates take into account price differences between countries for similar goods and services and thus reflect the underlying purchasing power (Kravits, Heston and Summers, 1982). A review of the PPP method and its uses is available in Schreyer and Koechlin (2002) and ICP (2007) contains the latest benchmark PPP rates.

2. Income distribution model and data sources

The current research draws on the Canback Global Income Distribution Database (C-GIDD, 2008). This database has two unique characteristics. First, it allows users to retrieve income data for arbitrarily chosen population or income brackets. Second, it contains data below national levels. Figure 4 illustrates these characteristics with an example from India.

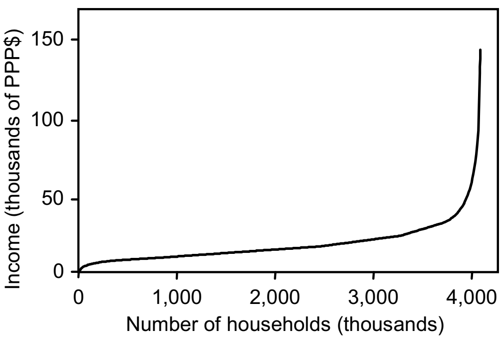


Fig. 4. Example of income distribution: Mumbai, 2008

The database was created in 1994 using national statistics and estimated income distributions through linear interpolation. The second version was introduced in 2005, again with national data but with more realistic income distributions using a method similar to Dikhanov and Ward (2001).

The third and current version was introduced in 2007 (see http://cgidd.com). It covers 211 countries, the largest 36 of which are partitioned into 506 subdivisions (states, provinces, etc.). It further covers 900 cities with more than 500,000 inhabitants as well as the remaining urban areas and rural areas. In total, the database includes more than 2,200 mutually exclusive geographic units[2] spanning the years 1990 till 2013. Table 1 shows an excerpt from C-GIDD.

Continuous income distributions have been estimated from household income bracket data. The function used is defined by: a) the integral of the function corresponds to the total household income in a given unit; b) the function differs by bracket. In the 0-10% population bracket (low income), it uses a logarithmic form; in the 10-90% brackets it uses spline functions; and in the 90-100% population bracket (high income) it uses a Gumbel-like function that reaches infinity at 100% yet has a finite area; c) the function is quasi-exact in Dikhanov and Ward's terms.

Moreover, the shapes of income distributions differ at national and subdivision levels in the database. This is because a country's national income distribution depends on both the income distribution within its subdivisions (or lower levels) and the difference in income between subdivisions.

The income distributions have additionally been used to estimate socioeconomic levels in each geographic unit. Based on a Mexican definition of socioeconomic levels (López Romo, 2005), the database contains the number of people and households belonging to the AB, C+, C, D+, D and E classes, respectively[3]. This analysis is done on an adjusted household-size basis to take into account that large households reap economies of scale and children tend to consume less than adults. The adjustment factor is the square root of the household size (Rainwater, 1974; Brown and Prus, 2003).

[1] Conversely, there is no reason to believe that market exchange rates can be used to compare the size of economies or the income of people since most products and services are not traded across borders and market exchange rates typically are fixed or semi-fixed.

[2] The Vatican; Western Sahara; Azad Kashmir and Northern Area in Pakistan; Chechnya in Russia, and Kingmen-Matsu Area in Taiwan are currently not part of the database.

[3] AB corresponds to upper class, C+ to upper middle class, C to middle class, D+ to lower middle class, D to lower class, and E to marginalized class.

Table 1. Sample data from C-GIDD: South Africa, 2008

		Population with income (PPP$)				Total population
Province	City or other area	< 2,000	2,000 - 4,000	4,000 - 8,000	> 8,000	
Eastern Cape	Port Elizabeth	227	274	293	230	1,024
	Other urban areas	646	560	404	264	1,874
	Rural areas	1,667	1,136	770	380	3,953
Free State	Urban areas	414	585	664	650	2,313
	Rural areas	149	175	180	126	630
Gauteng	Ekurhuleni	253	673	916	1,151	2,993
	Emfuleni	91	242	330	414	1,077
	Johannesburg	291	774	1,053	1,324	3,442
	Pretoria	59	217	346	721	1,343
	Other urban areas	151	182	194	151	678
	Rural areas	65	71	56	41	233
KwaZulu-Natal	Durban	458	690	785	800	2,733
	Other urban areas	632	682	530	391	2,235
	Rural areas	1,773	1,496	1,074	688	5,031
Limpopo	Urban areas	285	239	171	109	804
	Rural areas	1,972	1,313	871	418	4,574
Mpumalanga	Urban areas	353	425	453	353	1,584
	Rural areas	546	591	464	342	1,943
Northern Cape	Urban areas	202	246	267	217	932
	Rural areas	45	50	41	30	166
North-West	Urban areas	323	400	440	373	1,536
	Rural areas	491	545	471	341	1,848
Western Cape	Cape Town	154	551	855	1,661	3,221
	Other urban areas	162	311	372	423	1,268
	Rural areas	79	103	116	107	405
South Africa	Total country	11,490	12,531	12,116	11,707	47,844
	Major cities (7)	13%	27%	38%	54%	33%
	Other urban areas	28%	29%	29%	25%	28%
	Rural areas	59%	44%	33%	21%	39%

C-GIDD is populated with data from several sources. Among the more important sources are the UN for national population data, GDP and household income data; the IMF for short- and medium-term economic projections; the UN and the US Census Bureau for population projections; WIDER and national surveys for income distributions; Eurostat and national statistics offices for subdivision data; the UN, Eurostat, CityPopulation and national censuses for city data; and the ICP for PPP data.

Availability of city-level income data varies. In the US, EU, Brazil and a few smaller countries, availability is good. Further, China, India, and several other countries have data below the subdivision level (prefectures in China, districts in India) and cities typically dominate these sub-subdivisions. For such cities, income has been estimated based on a separate statistical analysis of the income gap between cities and their surrounding non-city areas. More than 700 of the 900 cities in the database consequently have solid income data.

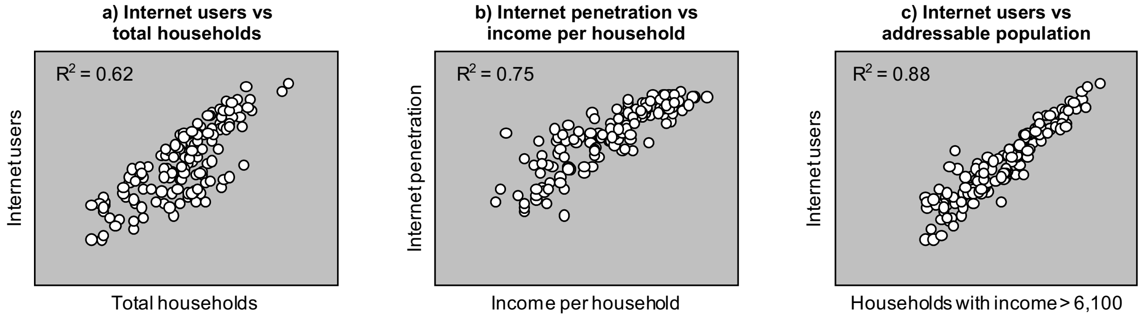
The remaining cities have been estimated based on the same statistical analysis as described above, but are not as well constrained by the surrounding area. For example, nine out of twelve Japanese cities are well-constrained by their subdivisions while three are not, leading to less precision in the latter estimates.

3. Results

In this section, we validate the hypothesis that using income distribution data (by income brackets and at the sub-national level) increases predictive accuracy for consumer demand models. We further discuss how the database can be used by practitioners. We start with basic findings and then move on to increasingly sophisticated applications according to the hierarchical levels in Figure 1, above.

3.1. Income distribution as a predictor of market size. The C-GIDD database provides a simple way to estimate the number of people with a given income. We can thus use the database to test the claim that income is a key determinant of demand for goods and services. Further, we can compare different income metrics to determine which is most closely correlated to actual demand.

Figure 5 shows a regression analysis between internet use and different explanatory variables of demand. First, Panel *a* shows the total number of households for 152 countries plotted against the number of internet users in each country. Not surprisingly, the number of users is higher in populous countries and number of households alone explains 57% of the variation in global internet use.



Note: Each data point represents one country (analysis includes 152 countries). Scales are logarithmic. PPP$ used.

Fig. 5. Comparison of market sizing variables and actual market size. Example: Internet usage, 2005

Second, because the cost of internet access may be prohibitive to many consumers, we reason that affluence may be important. Panel *b* confirms this assertion. Income per household (the average annual income per household within each country) explains 78% of the variation in internet penetration.

Third, we use the income distribution approach to calculate the number of households with annual income greater than a specified level (Panel *c*). We find that the best predictor of internet use is to think of the addressable market as those households that have an annual income higher than $6,100 (PPP). With this approach, 88% of the variance in global demand for internet use is explained.

Not surprisingly, there is a close relationship between income and demand. More importantly, we find that the income distribution approach has higher explanatory power than a method using average income as a metric.

The analysis was repeated for eleven other goods and services with similar results (Table 2). For each of these products and services, demand is better explained by the number of households above a certain cut-off income than by average income, as evidenced by the superior fit statistic. It is also worth noting how the cut-off income varies with the characteristics of the product or service analyzed.

It should be noted that these findings do not measure total causal effects. At this point of the discussion, income embeds information about unobserved demand drivers. When such drivers are incorporated into the analysis, the explanatory power of income is reduced. Yet the analysis demonstrates that knowing how many households can afford a certain product or service is an excellent starting point for sizing markets.

Table 2. Explanatory power of income on select products and services

	Fit (R^2)		Cut-off household income* (PPP$)
	Based on average income	Based on income distribution	
Airline passengers	0.65	0.73	12,100
ATM machines	0.65	0.84	4,700
Bank deposits	0.76	0.80	19,000
Electricity consumption	0.76	0.79	7,300
Insurance premiums	0.81	0.83	23,000
Internet users	0.75	0.88	6,100
McDonald's restaurants	0.69	0.86	21,000
Milk consumption	0.56	0.85	3,700
Mobile phone subscribers	0.70	0.89	4,700
Oil consumption	0.76	0.89	6,500
Personal computers	0.71	0.87	6,300
Television sets	0.57	0.93	2,900

* Household size adjusted using Rainwater's method (see Section 2, above)

3.2. Difference in growth of affluent consumers and GDP. Given that income is an important determinant of demand, C-GIDD may also be used to map the global consumer landscape over time. In fact, this analysis does much to explain the strategic focus of today's multinational consumer goods companies on emerging countries.

We extracted data from C-GIDD on how many people there were in 1998, 2008 and 2013 that could be considered affluent[1].

A slight majority of affluent households — those that regularly purchase branded, packaged products — currently live in the US, Canada, EU or Japan. How-

[1] For the purposes of this analysis, an affluent consumer is any person with purchasing power greater than that defined by the US poverty threshold ($16,218 for a family of 3 in 2007; http://www.census.gov).

ever, forward-looking executives must also seek out opportunities for continued growth. The share of the world's affluent households living in these countries will fall from 50% to 43% between 2008 and 2013.

This is almost entirely due to growth in Asia, whose share of affluent households will rise from 26% to 32% over the same period. With such a vast shift occurring in a relatively short span of time, the current preoccupation with emerging countries is understandable.

The shape of the income distribution (see example in Fig. 4, above) determines the speed with which new affluent consumers are being created. Because income is not distributed linearly throughout the population, growth in affluent consumers typically does not correspond to a country's overall economic growth rate. Growth in affluent consumers accelerates and decelerates as countries reach new stages of development.

For example, the number of affluent consumers in China has grown 15% per year over the last decade, during which time GDP has risen by 8% per year (Table 3). In contrast, the Czech Republic has seen annual GDP growth of 3.4% but only a 1.2% yearly growth in affluent consumers.

Table 3. Growth in GDP and affluent consumers for select countries, 1998-2008

	Real GDP growth (p.a.)	Growth in affluent consumers (p.a.)	Number of affluent consumers added (millions)
Brazil	3.0%	2.7%	17
China	7.9%	14.9%	120
Czech Rep.	3.4%	1.2%	1
Egypt	4.8%	6.2%	16
India	6.3%	9.9%	66
Russia	5.6%	4.8%	30
South Korea	4.7%	3.5%	13
Spain	3.3%	1.4%	5

The analysis demonstrates that markets often grow much faster than the overall economy in emerging countries. This explains why, for example, the Chinese cellular phone market has grown several times faster than the Chinese economy in this decade. In comparison with the growth of affluent and semi-affluent consumers, the cellular growth is perfectly reasonable.

3.3. Market sizing using income strata. The most straightforward strategic application of the income distribution approach is in generating market size estimates. To illustrate, we explored the market potential for a new health product to answer the following question: Is the opportunity for this product greater in China or in Brazil and Mexico combined?

Focus groups in each country indicated that interest and purchase intent was high amongst upper- and middle-class consumers. This stratum of consumers corresponds to the ABCD+ socioeconomic classes discussed in Section 2, above. An income distribution analysis was completed to calculate the size of the ABCD+ population.

Table 4 displays the results of this analysis. The ABCD+ population in the three countries is approximately 190 million. Brazil and Mexico combined have an ABCD+ population that is equal to that in China. This is the case even though the total combined population of Brazil and Mexico is roughly 25% of the total population of China. Since both Mexico and Brazil are more affluent countries than China, it is not surprising that the upper and middle classes form a larger portion of the population than in China.

Table 4. Population by socioeconomic level, 2008

	ABCD+ population living in:			Total ABCD+ population	ABCD+ population as a % of country total
	Large cities	Other urban areas	Rural areas		
Brazil	33.9	15.6	4.4	53.9	28%
China	56.6	12.0	21.0	89.6	7%
Mexico	32.4	9.8	5.4	47.6	45%

The benefit of the income distribution approach is that it transforms information regarding total or average affluence – which, at best, can give general qualitative insights about market opportunity — into a precise measure of the <u>number of consumers</u> who can be targeted.

An additional benefit is the ability to estimate regional differences within each country. In this analysis, we aggregated data from each country into three categories: large cities with population greater than 500,000; other urban areas with population less than 500,000; and rural areas.

We found that the ABCD+ population living in large cities is 57 million in China as compared to 66 million in Brazil and Mexico. Furthermore, we note that this population is spread across 192 large cities in China, whereas there are only 53 large cities in Brazil and Mexico combined. As such, the Brazil/Mexico market not only contains more potential consumers, but is also more concentrated in a smaller number of cities. Both of these factors are important considerations in determining where the opportunity is the greatest.

3.4. Category predictions with Golder-Tellis model. A more complex application to predict markets combines income distribution data with other salient data. As an example, we considered the market for a small appliance in Russia between 2004 and 2009. The Russian market had seen spectacular growth before 2004, but there was fear that it was about to be saturated.

To understand if this was happening, a pooled time series cross-section model (Podesta, 2000) based on the Golder-Tellis specification (discussed in Section 1, above) was built. It used income distribution data, product price, a consumer sentiment index, product availability and total category marketing spending (broken into promotional and advertising spending). The underlying dataset consisted of eight Russian cities and ten comparison countries.

Figure 6 displays the results of this analysis. The addressable population (defined here as households with PPP-adjusted income greater than $15,000) has a significant and positive correlation with demand for this small appliance in Russia. The relationship is strong, even with three other statistically significant variables in the analysis.

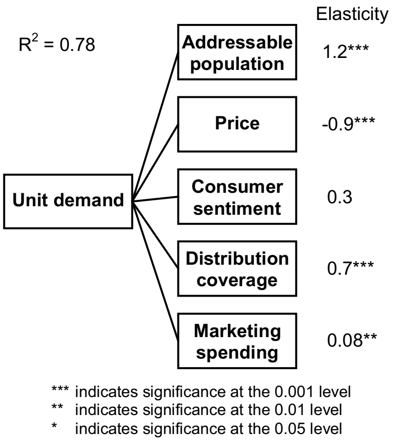


Fig. 6. Predictive model for a small appliance in Russia

Based on this model, it was reasonable to conclude that growth would continue to be high throughout the time period both in Moscow and in the regions. The main drivers were continued high growth in the affluent population that buy branded goods and rapidly increasing distribution coverage. The analysis did not suggest price cuts or increased marketing spending.

This application is useful for any marketing professional interested in predicting total category growth for a consumer product or service. The non-C-GIDD variables included in the Golder-Tellis model are readily available (e.g, from syndicated data providers and internal company tracking). Estimates of the category-specific variables (price, product availability, marketing spending) are fairly easy to extrapolate based on historical trends.

In sum, a Golder-Tellis model incorporating income distribution data provides a simple and accurate tool for predicting category demand. In this model, income can be seen as a non-influenceable exogenous driver rather than as the central driver of demand. Income is important, but so are the other drivers. Thus, this application is more realistic than the earlier applications discussed.

3.5. Quantifying demand drivers at the brand level by combing macro and micro data. An even more advanced application uses the Golder-Tellis model at the brand level and includes additional variables related to consumer behavior and competition. In this application, we are more interested in understanding what drives demand and which marketing levers to pull than in creating forecasts (although this is a natural extension).

The central idea is to combine macro-level data (e.g., income, price, distribution and marketing spending collected from C-GIDD, company databases and purchased third party data) with micro-level data (information on individual consumers gained through consumer surveys). This approach allows marketing professionals to build integrated models that take into account the levers within one integrated framework (Imbens and Lancaster, 1994).

Table 5. Demand drivers for a snack food in Argentina

	Demand driver	Metric	Impact	Comment
Influenceable	Price	Change in price	-1.10	Elasticity
	Marketing spending	Change in spending	0.10	Elasticity
	Distribution coverage			
	Kiosks and small trade	Change in numeric distribution	1.20	Elasticity
	Super/hypermarkets	Change in numeric distribution	0.80	Elasticity
	Product benefits			
	Health	One step improvement in Likert score (1-5)	0.19	Multiplier
	Convenience	One step improvement in Likert score (1-5)	0.08	Multiplier
	Taste	One step improvement in Likert score (1-5)	0.15	Multiplier
	New product introductions	Change in number of SKUs	0.04	Multiplier
Non-influenceable	*Socioeconomic level*			
	AB class	Change in no. of households	1.10	Elasticity
	C+ class	Change in no. of households	1.21	Elasticity
	CDE class	Change in no. of households	0.20	Elasticity
	Consumer sentiment	Absolute change in index (0-100)	0.002	Multiplier

To illustrate, we examined the market for a snack food in Argentina. Beginning with the base Golder-Tellis model, we added variables derived from a consumer survey conducted in Buenos Aires and from industry and trade interviews performed in the country. Table 5 reports the demand drivers for this integrated macro/micro model. The model has good fit and meets standard statistical tests.

The table requires a few explanations. First, several of the demand drivers are associated with elasticities. For example, if price is cut 10%, then demand may increase 11%; if distribution coverage in kiosks increases 10%, then demand is likely to increase 12%.

Second, some demand drivers use multipliers. This is because they are measured on ordinal scales and elasticities do not carry the same meaning for ordinals. An example is the health benefit of the product. Consumers were asked on a 5-point Likert scale to score exisiting products in the market. The multiplier was calculated by comparing these scores with actual consumption. On average, a one point difference in score resulted in a 19% change in consumption. A similar logic applies to the other multipliers.

Third, only some of the demand drivers are influenceable by a consumer goods company. It is useful to know that demand increases with income, but it is hard for a company to affect incomes. However, income is still an important part of the model, because without controlling for income, the other drivers will be incorrectly estimated.

The model shows that increasing consumer benefits through health and taste improvements is the strongest driver at the brand level. Further, strengthening distribution in the smaller trade is imperative while the modern trade channel, although important for food and beverages in Argentina, does not have as much impact on this snack food that is often bought on impulse. Finally, price sensitivity is fairly low. When the analysis is run without the socioeconomic levels (income), the price elasticity jumps to -2.1. That is, a 10% price decrease seems to generate 21% additional volume. But when income is correctly controlled for, the elasticity drops significantly. With a price elasticity of -1.1 and a marketing spending elasticity of 0.1, leveraging marketing and maintaining premium prices are the better strategic choices to make.

In sum, the examples discussed in this section illustrate how income distributions are helpful in quantifying markets and are an essential part of understanding the future market potential, especially in emerging countries.

Conclusion

This article described a new income distribution-based method to analyze demand for consumer goods in emerging countries. We also introduced a global income distribution database (C-GIDD) that allows this new method to be applied at sub-national levels, including cities. Our analyses have a number of implications for multinational consumer goods companies looking to capture opportunities in emerging countries.

First, we show the importance to global companies of knowing how many people have a certain income around the world — the *income distribution*. Any resource allocation decision needs to take into account the size of the potential market and the most fundamental variable that explains the size of a market is the number of people that can afford the product or service.

Second, we demonstrate that to measure these opportunities, detailed demand prediction models such as the Bass-Horsky or Golder-Tellis models require income data to be effective. It is only when income has been taken into account that other variables such as advertising or promotional spending on the supply side or consumer attitudes on the demand side can be estimated correctly.

Third, an important consideration when prioritizing among markets is the relative growth of different socioeconomic levels. We show that in an economy like China's, the growth of the middle class that buys branded products and services is much higher than the overall high economic growth. This implies that market entry decisions have to be made sooner than many companies believe.

Fourth, we demonstrate how income distribution data available at the macro level (e.g., cities) can be combined with micro-level (individual) data from consumer surveys to build robust predictive models. Such models allow marketing professionals to test assumptions for which claims to make in the market place and to prioritize among marketing levers.

Finally, implicit in our research is a belief that the use of simple models and consistent data is more valuable than complex approaches. The difficult part of strategy development or marketing efforts is the integration of often abstract information from a multitude of sources. Building predictive models anchored in income distribution is relatively easy and frees up time for professionals to focus on the integrative and more abstract aspects of their work.

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