Marketing Science Institute Working Paper Series 2016
Report No. 16-113

Wider Gaps in a Flatter World? The Speed of New Product Diffusion in Rich versus Poor Countries

Ashish Sood and Christophe Van den Bulte

Report Summary

Given the speed and extent of globalization, marketers need to understand how new products gain market acceptance in different countries. Whether the speed of new product diffusion has converged or diverged between rich and poor countries is an open question with important managerial implications.

In this report, Ashish Sood and Christophe Van den Bulte provide new insights by analyzing 848 diffusion trajectories of 15 consumer durables in 86 countries between 1977 and 2010. They address three questions:

1. Has the speed at which new products gain market acceptance evolved differently in rich and poor countries over the last four decades? Specifically, has the speed been converging or diverging?
2. Considering the possibility that the global convergence in consumer wants and the increased wealth in emerging economies are concentrated within the upper strata, does the pattern of convergence or divergence differ in the speed to reach 10% versus 50% household penetration?
3. Does the relation between income and diffusion speed differ across product categories?

Findings

Their analysis offers evidence that new product diffusion has accelerated, and that this acceleration is more pronounced in the speed to reach 50% than 10% penetration. However, there is no compelling evidence that diffusion speed to either 10% or 50% penetration has been *converging* between poor and rich countries between 1977 and 2010. Instead, the evidence clearly shows that diffusion speed for the time to 50% penetration has diverged between rich and poor countries over the last three decades (mirroring divergence in income levels between rich and poor countries). The gap between rich and poor countries in how quickly the top 10% adopts has neither widened nor narrowed.

This finding is at odds with Theodore Levitt's (1983) vision of increasing market globalization. It implies that marketers should take a more nuanced perspective, consistent with studies of demographic, intellectual, financial, and political dimensions that document continued fragmentation and heterogeneity across counties.

The authors note that some of their findings *may* be interpreted as consistent with the notion of increased homogenization and flattening of markets. Their findings of divergence in the speed to 50% but not 10% penetration raise the possibility that the "flattening" forces of improved infrastructure, improved communication, and increased homogenization have been more pronounced in the top 10% than the top 50% of the population.

Further, white goods diffuse differently than other consumer durables. Specifically, income gains do not appear to matter at all or may even decelerate the diffusion of white goods.

Overall, their analysis suggests that managers should be wary of forecasting how quickly a new product category will gain market traction in poor countries based on its speed of growth in rich countries. Such generalization may be safe if targeting only the top 10% of the population, but is likely to be very misleading for the median household. Managers need to exercise greater patience and make larger downward adjustments in penetration forecasts for poor vs. rich countries if they aim to reach beyond the upper strata into the middle of the income pyramid.

Further, when targeting markets experiencing strong growth in income per capita, managers should be mindful that growing income is associated with significant increased penetration growth for electronics and telecom, but not for home appliances.

Ashish Sood is Assistant Professor of Marketing, University of California Riverside. Christophe Van den Bulte is Gayfryd Steinberg Professor and Professor of Marketing, The Wharton School, University of Pennsylvania.

Acknowledgments
The authors benefited from comments by Raghuram Iyengar, Gerard Tellis, Pinar Yildirim, and session participants at the 2014 ISMS Marketing Science Conference, the 2015 AMA Winter Marketing Educators' Conference, and the 2015 EMAC Conference.

Introduction

Many markets and industries are steadily morphing into global arenas, and emerging economies are making growing contributions to global and corporate growth. The question whether developed and emerging markets are converging or diverging has become increasingly important to public and corporate policy (Jomo and Baudot 2007). "One of the most vexing debates about globalization," a recent study notes, "has to do with whether it produces convergence across countries or not" (Berry, Guillén and Hendi 2014, p. 387).

Globalization makes it increasingly important to know how new products gain market acceptance in different countries (Dekimpe, Parker and Sarvary 2000; Gatignon, Eliashberg and Robertson 1989; Peres, Muller, and Mahajan 2010). Yet, whether the speed at which new products diffuse has converged or diverged between rich and poor countries has very much remained an open question.

More than three decades ago, Levitt (1983) claimed that advances in communication and transportation technologies were driving the world toward "a converging commonality" where "[a]lmost everyone everywhere wants all the things they have heard about, seen, or experienced via the new technologies" (Levitt 1983, p. 92). This convergence of consumer wants, he claimed, resulted in the emergence of global markets in which new products would gain traction simultaneously throughout the world. The notion of a "flat world" of free-flowing information and global convergence in consumer wants was further popularized by Friedman (2005) and has become quite popular with executives and the general public over the years. It implies that new product diffusion patterns have become increasingly similar across countries since the 1980s.

Yet, knowing about a new product and wanting it is one thing, whereas being able to afford it is quite another. Even after controlling for differences in the cost of living, 97-98% of the population in India had a lower income than the poorest 1% of Germans in 2008. And the average income among the richest 1% in China was lower than the median in Germany (Milanovic 2015). Whatever truth there is in the notion of increasingly homogenous consumer wants across countries, there is little evidence of a similar global convergence in income levels across countries. There was no such convergence 30 years ago when Levitt wrote his landmark essay (Mankiw, Romer and Weil 1992; Sachs and Warner 1995; Sala-i-Martin 1996). And there still wasn't any 20 years later. As one textbook on macroeconomics put it at the time, "Unfortunately (from the perspective of the world's poor countries), there is little empirical support for … convergence. Most studies have uncovered little tendency for poor countries to catch up with rich ones" (Abel and Bernanke 2005, p. 235). Actually, inequality in countries' income per capita increased rather than decreased from 1980 to 2002 (Milanovic 2013).

Figure 1a shows how the average income per capita has evolved from 1977 to 2010, for 52 rich countries versus 137 poor countries. Income is GDP per capita measured in thousands of power purchasing parity (PPP) dollars, which controls for differences in the cost of a comparable bundle of goods over time and across countries. The divergence between rich and poor countries is striking. Figure 1b shows the same data, but for the log of income. The lines are parallel, with their slopes corresponding to a rather steady 2-3% growth rate in each group. Even though the proportional gap in income, corresponding to the ratio of the lines in Figure 1a and the distance between the lines in Figure 1b, stopped growing in 2000 and started to decline in 2005-2006, the difference in income grew steadily until the recession of 2008 and the gap has remained quite large, both in absolute and relative terms.

A lack of convergence has been observed in many dimensions besides income. Studies of changes along demographic, intellectual, financial, and political dimensions have found "fragmentation and continuing heterogeneity, that is, little evidence of convergence across countries over time" (Berry, Guillén and Hendi 2014, p. 388).

The absence of convergence in purchasing power raises doubts on the popular notion of convergence in new product diffusion patterns since the 1980s. Since the inequality across nations in GDP per capita has actually increased rather than decreased over most of the past 35 years, and income is a key correlate of diffusion speed, there is reason to expect that the speed of new product diffusion has diverged rather than converged between rich and poor countries.

The contrast between the popular discourse on market homogenization and the scientific evidence on divergence in purchasing power is striking. Given the importance of the question whether new product growth trajectories are converging or diverging across countries, the contrast is also disconcerting to marketers.

Of course, it is possible that incomes gaps have widened while at the same time the world has become flatter in other respects. Whereas income divergence is well documented, it is possible that convergence in consumer tastes, improvements in information flow across countries, and improvements in logistical infrastructure in emerging economies have been strong enough to neutralize or even overcome the effects of income divergence on diffusion patterns. The gaps in average income have widened across countries, but if the world has flattened, how has diffusion speed evolved in rich versus poor countries?

We provide new insights on this question by analyzing 848 diffusion trajectories of 15 consumer durables in 86 countries between 1977 and 2010. Specifically, we address three questions. (i) Has the speed of new product diffusion evolved differently in rich and poor countries over the last four decades? I.e., has it converged or diverged? (ii) Considering the possibility that the global convergence in consumer wants and the increased wealth in emerging economies are concentrated within the upper strata, does the pattern of convergence or divergence differ in the speed to reach 10% versus 50% household penetration? (iii) Does the relation between income and diffusion speed differ between appliances addressing functional needs ("white goods") and consumer electronics and IT products used mostly for leisure, since the latter are likely to have a higher income elasticity of consumption and a less concave Engel curve (Bonus 1973)?

In the process of answering these questions, we also present new evidence on two questions that have already been studied before. Has diffusion speed increased over time (e.g., Bayus 1992)? Is diffusion speed within a country associated with income inequality (e.g., Gelper and Stremersch 2014)?

We proceed by discussing related research, our measure of diffusion speed, and our database. We then present our findings from both model-free and statistical analyses. We conclude with a brief discussion.

Related Research

Several strands of research are relevant to our investigation. We first discuss research on the convergence or divergence of technological diffusion across countries. Next, we discuss research on diffusion acceleration, since convergence and divergence are driven by differences in changes in diffusion speed. Finally, we discuss research on income level and inequality as correlates of within-country diffusion speed.

Convergence and divergence

Two studies by Comin, Hobijn and Mestieri Ferrer are of particular interest, in spite of pertaining to production technologies rather than consumer products and covering the last two centuries rather than the last four decades. Using data on the diffusion of 15 technologies in 166 countries (830 technology-country pairs) over the last two centuries (1820-2003), Comin and Hobijn (2010) find that newer technologies start diffusing sooner than older ones did. They note that “This acceleration … has taken place during the whole two centuries that are covered by our data. Thus, it started long before the digital revolution or the postwar globalization process that might have contributed to the rapid diffusion of technologies in recent decades” (p. 2033). Specifically, acceleration is almost the same before and after 1950 (p. 2049).

Comin and Hobijn also find that new technologies start diffusing sooner in countries with higher income per capita (p. 2050). But that analysis of adoption lags across countries (differences in the time when diffusion starts) cannot provide insights on convergence vs. divergence in within-country diffusion speed because the “main assumption [they] use to identify the adoption lags is that the curvature of the diffusion curve is the same across countries” (p. 2050). In short, they assume perfect homogeneity across countries in the speed of within-country diffusion.

A more recent study by Comin and Mestieri Ferrer (2013) of 25 production technologies in 132 countries (1,306 technology-country pairs) over the last two centuries (1820-2003) documents that there has been convergence in adoption lags between rich and poor countries, while there has been divergence in usage intensity. I.e., while there is *convergence in the time at which new technologies start diffusing in each country, there is divergence in how quickly they gain usage within each country*. This clearly shows that (i) how soon a new product or technology starts diffusing in a market and (ii) how quickly it diffuses and gains market acceptance within that same market are very distinct phenomena—a point already made by Griliches (1957).

We are not aware of any study of diffusion convergence or divergence between rich and poor countries in the realm of new consumer products as opposed to technologies.

Acceleration

Several studies conclude that diffusion has accelerated within the U.S. (e.g., Agarwal and

Bayus 2002; Van den Bulte 2000). However, several others have found only mixed evidence or none at all (e.g., Bayus 1992). Moreover, estimation bias may have inflated some of the evidence of diffusion acceleration (Van den Bulte and Lilien 1997; Van den Bulte 2004).

Some studies involving multiple product and multiple countries conclude that diffusion has accelerated across products and countries. However, they use the first year in which sales or penetration data are available as a surrogate for the time of introduction, which can result in grossly overestimating the speed of subsequent diffusion (Chandrasekaran and Tellis 2007, p. 46). A study by Hartman, Mallick and Talukdar (2012) involving 4 products across 31 countries (124 product-country combinations) is not subject to this start-point problem, and finds no evidence of uniform acceleration.

In short, there is no compelling evidence yet of broad diffusion acceleration.

Income level and inequality as correlates of diffusion speed

Having reviewed findings on diffusion acceleration and convergence/divergence, we briefly discuss evidence of how income is related to diffusion speed.

Income per capita. Income per capita is a major predictor—and most likely causal driver—of new product diffusion speed (e.g., Gelper and Stremersch 2014; Van den Bulte 2000; Van Everdingen, Fok and Stremersch 2009). Nevertheless, some multi-country studies of speed very early in the diffusion cycle find no significant differences associated with income capita after controlling for other variables (Chandrasekaran and Tellis 2008; Tellis, Stremersch and Yin 2003). This is consistent with the notion that the 1% of the population adopting very early are part of a transnational global elite whose consumption behavior is disassociated from that of the other 99% of their country's population (Freedland 2011; Keegan and Green 2012).

Income inequality. Prior research provides no sound theory or evidence for a direct relation between diffusion speed and income inequality within a country. However, there is both theoretical support and meta-analytic evidence for a relation between the shape of the diffusion curve and income inequality (Russell 1980; Van den Bulte and Stremersch 2004). Specifically, if diffusion is driven or aided by price decreases, then diffusion trajectories in countries with higher income inequality should exhibit a more pronounced S-shape. High income inequality means that purchasing power is concentrated disproportionally among the wealthiest. Such countries may be quick in gaining some low level of penetration (Van Everdingen, Fok and Stremersch

2009) but slow in achieving 50% or more penetration. As Milanovic (2015) documents, income inequality matters for the income of the poor and of the rich within a country (in the opposite directions) but is of little importance to the middle class. This suggests that income inequality may have a different association with early vs. late diffusion speed. For instance, it may have a stronger association with the time to reach 10% penetration of the full population than 50% penetration.

White vs. other goods. If income is a key driver of new product acceptance, then categories with different income elasticities of consumption are expected to exhibit a different relation between income and diffusion speed (Bonus 1973). Specifically, the relation is expected to be weaker for white goods used within the home to address functional needs than for products used mostly for leisure or used conspicuously outside the home (Heffetz 2011).

Measuring Within-country Diffusion Speed

Definition

Everyday language conceives of speed as distance traveled divided by time of travel (e.g., 60 miles per hour) or, equivalently, the amount of time it takes to travel a particular distance. In the realm of diffusion, the distance pertains to the difference between two penetration levels. Hence, diffusion speed is the amount of time it takes to go from one penetration level to another (Van den Bulte 2000). A sound operationalization of speed requires start and end points to be defined and measured consistently.

Start point

An obvious choice of start point is the time at which the new product was introduced in a market and non-zero penetration became possible. Unfortunately, reliable information on introduction times is very rarely available even for developed economies. Van den Bulte (2000), for instance, notes how three different prior studies used three different times of introduction for microwave ovens in the U.S., varying by as much as 11 years.

Several studies use the first year for which sales or penetration data are available as a proxy for the time of introduction. This procedure is quite problematic. It tends to overestimate the time of introduction and hence underestimate the time it takes to reach the end point

(Chandrasekaran and Tellis 2007; Dekimpe, Parker and Sarvary 2000). The procedure also affects the parameter estimates of diffusion models requiring correct knowledge of the time of introduction (Dekimpe, Parker and Sarvary 1998; Jiang, Bass and Bass 2006) and hence affects any speed metric computed from such parameter estimates (e.g., the time to peak adoption in the Bass model). The problem is especially acute in studies of diffusion comparing countries with different levels of economic development, for two reasons. First, the delay in the collection of sales or penetration data is likely to be greater in less developed economies, making the downward bias in computed and inferred durations greater in those countries. This difference in bias will make the average difference in speed between rich and poor countries seem smaller than it is. Second, if improvements in data collection over the data window are greater in poor than rich countries, then the downward bias will decline more for poor than rich countries. This difference in the change in bias will make the convergence between poor and rich appear smaller, or the divergence greater, than it truly is.

To avoid these problems, we operationalize the start point in terms of a non-zero penetration level that is applied consistently across all products and all countries, as advocated by Dekimpe, Parker and Sarvary (1998, 2000) and Van den Bulte (2000). Specifically, we define the start point as the year in which the new product reached 1% penetration in the country of interest. That information is available for many more data series than the year of introduction. We exclude all product-country combinations for which we do not observe when 1% penetration was reached. Though such left-truncation affects the sample over which we can draw inferences, it does *not* create a statistical bias in hazard models (Van den Bulte and Iyengar 2011, p. 233).

End point

Prior analyses of diffusion speed use a variety of end points. These can be organized along two dimensions. The first is whether the end point is defined conditional on a model-based market ceiling or directly in terms of data. The second is whether the end point is defined in terms of a penetration level or in terms of a kink, inflection, or turning point in the diffusion trajectory. Of the four possible combinations, we choose to define end points in terms of penetration levels observed directly from data. As other combinations have been used in prior research, we discuss the rationale for this decision.[1]

Conditioning on a model-based ceiling is attractive when one wants to distinguish between the effects of covariates on the ceiling versus the growth rate (e.g., Dekimpe, Parker and Sarvary 1998) or when one's theory pertains only to the model's scale or shape parameters (e.g., Van den Bulte and Stremersch 2004). It is less relevant when studying cross-country convergence and divergence between rich and poor countries since marketers, policy makers and globalization scholars are typically interested in how quickly new products penetrate the overall population. Given our main research question, we prefer a metric of speed that captures penetration gains stemming from changes at both the extensive margin (ceiling) and the intensive margin (growth rate given a ceiling). Using a speed metric that does not require estimating a ceiling also avoids the risk of having the metric be affected by estimation biases (Van den Bulte and Lilien 1997; Van den Bulte 2004). Since these biases are larger for shorter data series, and since data series tend to be shorter for poor countries and for more recent products, the concern is that biased diffusion model estimates will erroneously steer one's findings towards greater acceleration in poor than in rich countries. That would bias one's conclusions towards (i) convergence if poor countries are inferred to close an initial gap, (ii) divergence if there is no initial gap, or (iii) convergence followed by divergence if the bias is greater than the initial gap.

End times that are not conditional on a model-based ceiling can be defined either in terms of a kink or inflection in the raw data (e.g., Agarwal and Bayus 2002; Tellis, Stremersch and Yin 2003; Van Everdingen, Fok and Stremersch 2009) or of a specific penetration level (e.g., Chandrasekaran and Tellis 2008; Cox and Alm 1996; Getz, Seigfried and Anderson1997). We prefer the latter because unambiguous penetration levels are more relevant to marketers, policy makers and globalization scholars whose interest is in how quickly new products penetrate the overall population in rich vs. poor countries rather than in the presence and location of kinks and turning points in diffusion trajectories.

[1] Examples of end points conditional on a model-based ceiling and defined in terms of a kink or inflection include the time of peak adoption in the Bass model (e.g., Bayus 1992) and the time of peak acceleration in adoptions in the Bass model (e.g., Lim, Choi and Park 2003). An example of an end point conditional on a model-based ceiling and defined in terms of a penetration level is the take-over time in the logistic model (e.g., Van den Bulte 2000). Studies of take-off often define the end point based on a kink in the actual (model-free) diffusion trajectory (e.g., Tellis, Stremersch and Yin 2003).

We use not one but two end times: the years in which 10% and in which 50% penetration was reached. This provides insights on both early and overall diffusion speed, which may relate differently to some country and products characteristics.

Data

This section describes the data sources, procedure, and measures used to construct a data set covering 15 products, 86 countries, and 34 years (1977-2010).

Penetration data

The penetration data comprise annual observations of the fraction of all households in a country who own a particular product. These data are sourced from the Global Market Information Database (GMID) maintained and distributed by Euromonitor International. We use the following rules to select and purify the data for subsequent analysis. First, as described earlier and in line with prior research (Sood, James and Tellis 2009; Van den Bulte 2000), we retain only those series where the penetration level in the first year of available data is lower than 1%. Second, we censor all data series when they reach a preset penetration level (10% or 50%, respectively). Third, we supplement the data with public information on the global launch of CD players and DVD players, and with information on the year of launch of mobile telephones in each country, kindly supplied to us by Philip Parker. This additional information allows us to identify the first year that a product-country combination reached 1% penetration for a few more combinations than is possible from the GMID data alone. Fourth, we exclude product categories that are old by Western standards and had already reached 1% penetration in the very great majority of rich countries by 1977 (e.g., black & white television sets, vacuum cleaners, and washing machines). Excluding these older categories makes the rich and poor countries more comparable in the products we study. This balance, in turn, reduces the risk of confounding differences in speed across rich and poor countries with differences across products.

Table 1 lists the 86 countries included in this study. The rich or high-income category includes the 37 high-income countries according to the 2012 World Bank classification as well as Taiwan, which is not classified. The remaining 48 countries, which we label poor or low-income, are middle-income countries according to the World Bank. None of the very poorest countries labelled low-income by the World Bank (e.g., Burkina Faso, North Korea and Somalia) appears in the GMID penetration data. Table 1 also lists the 15 product categories covered by our data. The income evolution in rich and poor countries among those 86 countries is in essence identical to that shown in Figure 1 for all countries (See Appendix for details).

Table 2 lists the 15 products included in this study. For each of those products, it also reports the number of countries covered as well as the fraction of countries covered that are rich. It does so for the full data set of 848 product-country combinations, as well as for two sub-sets. The first, labeled GT10, consists of the 693 product-country combinations for which 10% penetration does not fall below the 95% confidence bound of the Bass model ceiling estimate.[2] The second, labeled GT50, consists of the 381 product-country combinations for which 50% penetration does not fall below the 95% confidence bound of the Bass model ceiling estimate. These two smaller data sets are created to check whether the key findings are robust to excluding product-country combinations that are unlikely to ever reach the threshold value of 10% or 50%. The fraction of product-country combinations stemming from rich countries is quite similar between the full and GT10 data sets, but is notably higher in the GT50 data set. However, within each data set, the fraction of observations stemming from rich countries tends to vary within a +/- 20% bound from the average.

Income variables

Income level. To allow for comparisons across countries and over time, we measure income per capita (*Income*) as the PPP (purchasing power parity) converted GDP per capita (in $100,000) at 2005 constant prices. We use the "rgdpch" series published in the Penn World Table version 7.1 (Heston, Summer and Aten 2012). To distinguish between the variation in income within and across countries, we define the time-invariant *Inc2000* as the country's *Income* in the year 2000 and the time-varying *IncDiff* as the country's *Income* centered on *Inc2000*.

High- vs. low-income. The high-income group includes Taiwan and countries classified as high-income countries by the World Bank in 2012. The low-income group includes all other

[2] For each of the 848 data series, we estimated a Bass model using nonlinear least squares and all available penetration data between 1977 and 2010. We estimated the discrete-time difference equation version of the model because it does not require or knowing the "time zero" when each product became available in each country and hence avoids truncation biases (Jiang, Bass and Bass 2006; Lilien, Rangaswamy and Van den Bulte 2000).

countries. The dummy variable *Hi* indicates group membership. So, in models where variables are interacted with *Hi*, the lower-order terms refer to the low-income countries.

Income inequality. As our measure of income inequality, we use the *Gini* coefficient reported in Euromonitor's Global Market Information Database. When multiple values are available for a country, we linearly interpolate between the years. Outside the interval, we use the value reported for the nearest year (Van den Bulte and Stremersch 2004).

White goods

We coded the following products as white goods: Air Conditioner, Dishwasher, Freezer, Microwave Oven, Refrigerator, Tumble Drier, Vacuum Cleaner, and Washing Machine. For these categories, the binary indicator *WG* is 1. For others, it is 0.

Model-free Analyses

We start with documenting differences in speed and patterns of convergence or divergence between high- and low-income countries. For expositional fluency, we refer to these two groups as rich and poor countries.

Average speed in rich vs. poor countries

We first assess whether the speed at which 10% and 50% penetration is reached differs between rich and poor countries. For this analysis, our data includes 86 countries, 15 products, and 848 product-country combinations. The product-limit or Kaplan-Meier estimator provides non-parametric tests, be it while ignoring the presence of repeated observations across countries and countries. As expected, both 10% and 50% penetration is reached faster in rich than in poor countries ($p < .001$, consistent across log-rank, Wilcoxon and likelihood ratio tests).

Acceleration and convergence/divergence

Of greater interest is whether the speed of reaching 10% and 50% penetration has increased over time, and has done so differently between rich and poor countries. Simply plotting how the observed time to go from 1% to 10% or 50% penetration has evolved over time suffers from truncation biases. It is more informative to graph the empirical hazard rate, i.e., the fraction of data series that reach 10% (or 50%) in a given year given that they have not done so before (e.g., Hu and Van den Bulte 2014; Iyengar, Van den Bulte and Valente 2011). Unlike plots of observed durations, empirical hazard rate plots do not exclude product-country combinations that were too slow to reach 10% or 50% by 2010, the end of our data window.

We plot the empirical hazard rates against all three dimensions of time: calendar time, vintage or cohort, and age. *Calendar Time* or *Year* is the year of observation. *Vintage* is the year in which the product-country combination reached 1% penetration. *Age* is the number of years that have passed since the product-country combination reached 1% penetration: *Age* = *Calendar Time – Vintage*.

Figure 2a plots the 10% empirical hazards against calendar time, for both rich and poor countries, in the Full data set. The graph exhibits four patterns, suggesting four conclusions. First, the hazards are higher in rich than poor countries, so diffusion is faster in the former. Second, the hazards increase over time. This is consistent with genuine acceleration over calendar time, but may also reflect positive duration dependence, i.e., the notion that hazards increase with age, which is consistent with S-shaped diffusion curves typically observed for consumer durables. Third, the gap with poor countries barely increases between 1977 and 2000. Hence, there is no clear convergence or divergence in the speed to 10% in that period. Fourth, there is some evidence of convergence after 2000-2003. Figure 2d reports the same empirical hazards for the GT10 data set, and corroborates the first three patterns.

Figure 2b plots the 10% empirical hazards against vintage, for both rich and poor countries, in the Full data set. The plots indicate that the speed is higher in rich countries, but do not exhibit any compelling pattern consistent with acceleration, divergence, or convergence. Figure 2e suggests some acceleration in the GT10 data set, but again without clear convergence or divergence.

Figures 2c and 2f, finally, plot the hazard of reaching 10% against age, in the Full and GT10 sets, respectively. The speed is higher in rich countries, and there is evidence of an inverse-U pattern in duration dependence.

The patterns in the speed to reach 50% penetration are somewhat different, at least when considered against calendar time. Figure 3a plots the 50% empirical hazards against calendar time, for both rich and poor countries, in the Full data set. The graph exhibits three patterns, suggesting three conclusions. First, the hazards are higher in rich than poor countries. Second, the hazards increase over time. Third, the gap between rich and poor countries seems to increase over time. This evidence of divergence is more pronounced in the GT50 data set (Figure 3d).

Figures 3b and 3e, showing speed against vintage, show only weak evidence of acceleration, and no evidence of convergence or divergence in either the Full or GT50 data sets. Figures 3c and 3f exhibit a slight inverse-U pattern of speed to 50% against age, but no indication of acceleration, convergence, or divergence.

Conclusion from the model-free analysis

The data indicate not only that new product diffusion is faster in rich than poor countries and that diffusion has accelerated over time on average, but also that the speed to 50% has accelerated more in rich than poor countries. This difference in both initial position and subsequent change amounts to divergence rather than convergence in the speed to 50%. The speed to reaching 10%, in contrast, has accelerated but without any consistent divergence or convergence, though there is some suggestive evidence of a regime shift around 2000.

Given the popularity in prior research of using model-based ceilings, we emphasize that these conclusions are robust to defining the population of adopters either as the full population or as the upper 95% of the Bass diffusion ceiling.

Statistical Modeling Approach

Motivation

The empirical hazard plots provide suggestive evidence of acceleration and divergence, but without any information on whether the patterns in the data are stronger than what can be expected from chance alone. Moreover, the plots do not control for the absence of perfect balance in the data base. First, even though the fraction of observation coming from rich vs. poor countries varies in a fairly narrow range, it is not identical across products. Second, rich countries are observed throughout the data window, whereas diffusion data series from poor countries tend to start later and hence be shorter. In the absence of perfect balance, focusing on changes that occur *within* countries and *within* products provides a more stringent test of acceleration and convergence/divergence. This can be achieved by controlling for fixed effects for each country and for each product. Random effects do not provide as stringent a control because, unlike fixed effects, they are assumed to be orthogonal to the included covariates (Wooldridge 2002, p. 252).

Linear vs. logit hazard models

We organize our data in a standard discrete-time panel data set-up. We do so for 10% and 50% penetration separately. We create a binary indicator variable Y_{ijt}, indicating whether product *i* has reached the critical penetration level in country *j* in year *t*. Each product-country combination receives as many lines as there are observations until the critical level is reached or the data are censored. Once the data are organized as a panel, we estimate hazard models using both a linear probability and a logit model specification.[3]

The linear model's slope coefficients give the expected change in the hazard associated with a one-unit change of the covariates, and are unbiased in the presence of fixed effects. That the predicted values may fall outside the unit interval is immaterial here, since we are interested in patterns of acceleration and divergence/convergence that hold across products and countries rather than in predictions of the hazard for any individual product-country-year combination. The logit hazard model provides such bounded predictions, but suffers from three disadvantages for the purpose of our analysis. We discuss each in turn.

Interaction artefacts. The logit model does not provide us with the information wanted, as its slope coefficients quantify the expected change in the log-odds of the hazard, rather than in the hazard itself, associated with a one-unit change of the covariates[4]. This distinction can greatly affect research conclusions about the presence and size of interactions. To illustrate consider the pattern in Figure 4a. It shows two lines, exhibiting a pattern similar to that in the empirical hazards. By Berkson's Interocular Traumatic Test criterion, "You know what the data mean when the conclusion hits you between the eyes" (Edwards, Lindman, and Savage 1963, p. 217), the two curves are diverging. However, the two lines are logistic curves with exactly the same slope coefficient or shape parameter. They differ only in their intercept or location parameter.

[3] When computing standard errors of the linear probability models, we account for its inherent heteroscedasticity (Cheung 2007; Wooldridge 2002, p. 454).

[4] Computing marginal effects in linear space and their standard errors for a logit model is possible, but requires additional assumptions making one's conclusions more tenuous than those of a linear model (Angrist and Pischke 2009, p. 107). Rather surprisingly, a significant coefficient of a product term between two variables in log-odds space is neither a necessary nor a sufficient condition for a significant cross derivative of the probability with respect to two covariates in linear space, and the two quantities can even have opposite signs (Ai and Norton 2003).

Figure 4b illustrates the opposite phenomenon: Two parallel lines with different logit slopes. Hence, comparing countries based on how the log-odds of their diffusion hazard increases over time can lead to conclusions that are inconsistent with the commonplace conception of convergence/divergence.

That interactions differ when examined on the linear scale versus the log-odds scale has long been recognized (e.g., Rothman, Greenland and Walker 1980). Specifically, logit modeling is often unable to detect interactions on the original additive scale, though false positives are also possible. Several methodologists therefore recommend using the additive scale only, or reporting results on both the linear and (log-)odds scales (e.g., Cheung 2007; Greenland and Rothman 1998; Hernandez and Blazer 2006; Knol et al. 2009; Szklo and Nieto 2000; Vandenbroucke et al. 2007). We follow that recommendation.

Incidental parameters problem. The logit model with fixed effects suffers from an incidental parameters problem, making the maximum likelihood estimates of substantive interest inconsistent (Wooldridge 2002, pp. 484 and 490-492). The usual solution, using Chamberlain's conditional ML approach, does not apply to models with crossed fixed effects for both countries and products.

Quasi-complete separation. Finally, the logit model suffers from quasi-complete separation when applied to our data. For example, we never observe any product going from 1% to 50% penetration in India and the same holds for Kazakhstan, Montenegro, Turkmenistan and Uzbekistan when we require income data to be available starting from the year 1% penetration was reached. As a result, the log-likelihood would reach its true maximum only when the estimates of the relevant fixed effects reached $-\infty$. Since the observations to which those fixed effects pertain would then provide no information about the other parameters, one can as well delete them from the data set, delete their dummy variables from the model, and proceed as usual. Though this approach and a variant thereof have proved useful in prior work where the deletions were unlikely to affect the findings of substantive interest (e.g., Iyengar, Van den Bulte and Lee 2015), they are problematic in our analysis. Excluding some poor countries because they exhibit very slow diffusion is likely to make the included poor countries more similar in speed to the rich countries, and would consequently bias the logit estimates towards convergence and against divergence.[5]

Statistical Analysis of Convergence/Divergence

Analysis for speed to 10%

We first estimate a set of models involving only the three time dimensions used in the model-free analysis (Calendar Time, Vintage, and Age), the coefficients of which we allow to differ for rich vs. poor countries, and fixed effects for each country and each product. We estimate three linear hazard models (Models 1-3) and their logit counterpart (Models 4-6). Model 1 is a linear regression model featuring only the effect of *Year* (i.e., *Calendar Time*), which is allowed to differ depending on whether country *j* is high- or low-income as defined before (*Hi*), and fixed effects for each country and each product. Model 2 extends Model 1 by incorporating *Vintage* and *Vintage* × *Hi*. Model 3 extends Model 1 by incorporating *Age*, *Age* × *Hi*, Age^2 and $Age^2 \times Hi$. Based on the plots, we expect age to have a non-monotonic association. Since *Age* = *Calendar Time* – *Vintage*, a model including all three time dimensions is not identified.

Models 1-3 are estimated using OLS, with Huber-White robust errors to account for the inherent heteroscedasticty of linear probability models. Models 4-6 are the logit counterparts of models 1-3 and are estimated using maximum likelihood. In all statistical models that follow, *Year* and *Vintage* are centered at 1976.

Simplest models. Table 3 reports the model estimates for all 848 product-country combinations. The positive Year coefficients in Models 1-2 and 4-5 indicate that the hazard increased over time, but this evidence of acceleration vanishes after controlling for age effects (Models 3 and 6). The coefficients of *Year* × *Hi* are not significantly positive or negative in any consistent way, so there is no robust evidence of either convergence or divergence. This is consistent with the empirical hazard plots (Figure 2a).

The *Vintage* effects in Table 3 are negative (Models 2 and 5). Since the models include fixed effects for countries and for products, this indicates that, in a given country, products that

[5] Chamberlain's conditional ML approach, if it were applicable, would suffer from the same problem. It excludes all groups (e.g., countries) where the dependent variable is always 0 or always 1.

reach 1% relatively late tend to be also relatively slow in subsequently going from 1% to 10%. Similarly, it indicates that, for a given product, countries that reach 1% relatively late tend to be also relatively slow in subsequently going from 1% to 10%. Of particular note are the negative coefficients of *Year* × *Hi*. This indicates that the negative vintage pattern is more pronounced in rich than in poor countries, which is consistent with convergence in *Vintage*. But, this is offset by evidence of divergence in Calendar Time (*Year*) in those same Models 2 and 5, which is consistent with the overall nil effect of *Year* × *Hi* in Models 1 and 4.

Age has an inverse-U association with the hazard of reaching 10% (Models 3 and 6). This is consistent with the empirical hazard plots (Figure 2e).

Richer models. We next enrich the six models in two ways. First, we allow the baseline hazards to differ before and after 2000 by adding the binary indicator *D2000*. Second, we replace the binary indicator *Hi* by *Inc2000*, the GDP per capita in 2000. The latter protects us from artefacts about convergence or divergence stemming from defining poor and rich countries based on income differences in 2012 only, or from using a dichotomized moderator (Irwin and McClelland 2003).

Table 4 reports the model estimates of the coefficients of central interest. The negative coefficients of *D2000* in the linear models (1-3) indicate that the baseline diffusion speed was lower after 2000, but such evidence of deceleration is not present in the logit model estimates. Nor is there robust evidence of deceleration or acceleration *within* the period 1977-1999: the coefficients *Year_pre* (i.e., the coefficient of *Year* when year < 2000) shows no consistent pattern across models. In contrast, the coefficients of *Year_post* (i.e., the coefficient of *Year* when year ≥ 2000) are positive in five of six models, providing rather robust evidence of acceleration within the period 2000-2010.

For evidence of convergence or divergence, we turn to inspecting the interactions between temporal variables like *D2000* and *Year*, on the one hand, and *Inc2000* on the other. The interaction between *D2000* and *Inc2000* is significantly positive in all six models, providing robust evidence of divergence in baseline speed after 2000. This is very different than what is suggested by the empirical hazard plots in Figure 2a, which do not control for fixed product and country effects. Focusing on trends within the periods 1977-1999 and 2000-2010, reflected in the interactions of *Year_pre* and *Year_post* with *Inc2000*, there is no evidence of either convergence or divergence that is consistent across models.

Models with Income. Finally, we extend the models in Table 4 with *IncDiff* (the average income in a country and year centered around the average income in that country in 2000) and *Gini*, while allowing their associations with diffusion speed to differ between white goods (*WG* = 1) and other products (*WG* = 0).

Table 5 reports the model estimates of the coefficients of central interest. Income growth within a country is associated with higher diffusion speed in four of the six models. Income inequality, as reflected in the Gini coefficient, is not robustly associated with the speed to reach 10% penetration, and the associations of income level and income inequality with diffusion speed do not differ consistently between white goods and other categories.

Controlling for income growth and income inequality has little effect on the conclusions from the prior analysis. Specifically, the results in Table 5 still provide rather robust evidence of acceleration within the 2000-2010 period, only weak evidence of acceleration within the 1977-1999 period (Models 1-2 and 4-5), and no robust evidence whatsoever of either convergence or divergence within the periods 1977-1999 or 2000-2010.

Conclusion about speed to 10%. Overall, there is (i) fair evidence of acceleration throughout the period 1977-2010, and (ii) strong evidence of acceleration after 2000 especially. There is (iii) suggestive evidence that income growth is positively associated with increases in diffusion speed within countries, but the evidence is statistically significant in only four of six models. Finally, there is (iv) no compelling evidence of either convergence or divergence, either before or after controlling for income growth.

Robustness to use of model-base ceiling instead of full population. The merely suggestive evidence for conclusion (iii) is weakened even more when we estimate the same set of models on only those product-country combinations for which 10% is not higher than the 95% confidence interval of the Bass model ceiling estimate (see Appendix). The number of models providing evidence of income growth being associated with diffusion decreases from four to only two out of six. This change could be consistent with the notion that income affects the diffusion ceiling and does so more than it affects the speed at which this ceiling is reached (e.g., Dekimpe, Parker and Sarvary 1998). However, the other three conclusions are robust, including (iv) on the lack of compelling of evidence for either convergence or divergence.

Analysis for speed to 50%

We repeat the analyses reported above, but now for the speed at which 50% penetration is reached.

Simplest models. Table 6 reports the simplest models' estimates for all 848 product-country combinations. The positive *Year* coefficients in Models 1-2 and 4-6 provide nearly entirely robust evidence of acceleration over the window 1977-2010 in poor countries. Adding the coefficients of *Year* and *Year* × *Hi* indicates acceleration in all rich countries. In contrast, the coefficients of *Year* × *Hi* provide no robust evidence of either convergence or divergence. This is consistent with the empirical hazard plots in Figure 3a.

The *Vintage* effects are negative in poor countries (Models 2 and 5), and for rich countries as well in the logit model. The significantly positive coefficient of *Vintage* × *Hi* in the linear Model (2) is consistent with divergence, but the logit Model (5) does not corroborate that. As with the speed to 10%, *Age* has an inverse-U association with the hazard of reaching 50% (Models 3 and 6). This is consistent with the empirical hazard plots in Figure 3e.

Richer models. We next enrich the six models by allowing the baseline hazards to differ before and after 2000 and by replacing the binary group indicator *Hi* by the more fine-grained *Inc2000*, the GDP per capita in 2000. Table 7 reports the model estimates of the coefficients of central interest. The negative coefficients of *D2000* in all six models indicate that the baseline diffusion speed in poor countries was lower after 2000. However, this evidence of deceleration across the 1977-1990 and 2000-2010 periods is paired in five of the six models with evidence of acceleration *within* the period 2000-2010, as indicated by the positive coefficients of *Year_post* (i.e., the coefficient of *Year* when year ≥ 2000). There is no compellingly robust evidence of acceleration or deceleration trend within the 1977-1999 period.

As to the question of convergence and divergence, both the linear and logit models provide evidence of divergence, but of a different kind. The significant positive interactions between *Year_pre* and *Inc2000* in linear Models 1-3 provide evidence of divergence with the 1977-1999 period, whereas the significant positive interactions between *D2000* and *Inc2000* in logit Models 4-6 provide evidence of divergence in baseline speed across the periods 1977-1999 and 2000-2010.

Models with Income. Finally, we extend the models in Table 7 with *IncDiff* and *Gini*, while allowing their associations with diffusion speed to differ between white goods and other products. Table 8 reports the model estimates of the coefficients of central interest.

Income growth within a country is associated with higher diffusion speed of non-white goods in only half of the six models. Of note is that four of the six models indicate that the association of income growth with speed to reach 50% is markedly lower for white goods than other products, consistent with the notion that the diffusion of discretionary non-white good should exhibit greater income effects than that of white goods (Bonus 1973). Income inequality, as reflected in the Gini coefficient, is not robustly associated with the speed to reach 50% penetration

Comparing the coefficients of *Year_post* in Tables 7 and 8 shows that controlling for income growth and income inequality has little effect on the evidence of acceleration after 2000. That indicates that income growth is *not* the sole explanation for the increase in speed to reach 50%.

Comparing the interactions of *Year_pre* and *Year_post* with *Inc2000* in Tables 7 and 8 informs us about to what extent the presence or absence of convergence or divergence can be attributed solely to income growth. Two patterns emerge. First, whereas the coefficient of *Year_pre* × *Inc2000* was significantly positive in all three linear models (1-3) in Table 7 before controlling for income growth, only one remains so in Table 8. Second, whereas the coefficient of *Year_post* × *Inc2000* was not significantly negative in any model in Table 7 before controlling for income growth, it is so in three of the six models in Table 8. These patterns do not document but at least suggest two patterns in the data. First, the divergence in income growth has contributed to the divergence in the speed to reach 50% penetration. Second, aside from income growth, there are unobserved trends that tend to make diffusion speed converge rather than diverge across rich and poor countries.

Conclusion about speed to 50%. Overall, there is (i) robust evidence of acceleration throughout the period 1977-2010 in both rich and poor countries, and (ii) robust evidence of acceleration after 2000 especially, again in both rich and poor countries. There is (iii) suggestive evidence that income growth is positively associated with increases in diffusion speed within countries, but the evidence is statistically significant in only three of six models and does not generalize to white goods. Further, there is (iv) evidence of divergence, both before and after

2000, but the nature of the evidence differs across linear and logit models. Finally, the evidence suggest that (v) the divergence in income growth has contributed to the divergence in the speed to reach 50% penetration and that (vi) aside from income growth, there are unobserved trends that tend to make diffusion speed converge rather than diverge across rich and poor countries.

Robustness to use of model-base ceiling instead of full population. We checked to what extent these conclusions are robust to estimating the same set of models on only those product-country combinations for which 50% penetration is not higher than the 95% confidence interval of the Bass model ceiling estimate (Appendix). Conclusions (i) and (ii) about acceleration were quite robust. Conclusion (iii) about income growth does not hold entirely: In the alternative analysis, we find no association anymore between income growth and speed to 50% for non-white goods—a change consistent with the notion that income affects the diffusion ceiling and affects it more than the speed at which this ceiling is reached (e.g., Dekimpe, Parker and Sarvary 1998)—but find stronger evidence that income growth matters less for white goods than for non-white goods—consistent with standard Engle curve analysis (Bonus 1973). More importantly given our research objectives, conclusion (iv) about the presence and nature of divergence was fully corroborated, and conclusions (v) and (vi) were corroborated, be it less compellingly, in that the coefficients of Year_pre × Inc2000 and Year_post × Inc2000 were smaller (less positive or more negative) after controlling for income growth.

Discussion

Our study of the speed of diffusion of 15 consumer durables across 86 countries between 1977 and 2010 provides several new insights. We briefly review and discuss them.

Implications for diffusion theory and research

Convergence/Divergence. There is no compelling evidence that diffusion speed to either 10% or 50% penetration has been converging between poor and rich countries between 1977 and 2010. Instead, the evidence clearly points that diffusion speed has diverged rather than converged between rich and poor countries over the last three decades. So, the divergence in income levels between rich and poor countries is mirrored in how quickly new products gain market acceptance. Of particular note is that divergence is observed only for the time to 50%

penetration. The gap between rich and poor countries in how quickly the top 10% adopts has neither widened nor narrowed.

Our main finding is very much at odds with Levitt's (1983) vision of increasing market globalization. It implies that marketers should take a more nuanced perspective, consistent with studies of changes along demographic, intellectual, financial, and political dimensions documenting continued fragmentation and heterogeneity across counties, with little evidence of convergence (Berry, Guillén and Hendi 2014, p. 388).

However, some of our findings *may* be interpreted as consistent with the notion of increased homogenization and flattening of markets. First, while our analysis indicates that the divergence in income growth has contributed to the divergence in the speed to reach 50% penetration, it also indicates that, aside from income growth, there are unobserved trends that tend to make diffusion speed to 50% converge rather than diverge across rich and poor countries. These unobserved trends might include advances in communication and transportation technologies and converging consumer wants. Second, the presence of evidence of divergence for speed to 50% penetration combined with the lack of evidence of either divergence or convergence for 10% penetration can be seen as consistent with the notion that, already in the early 1980s, the 10% of the population adopting first were part of a transnational "global elite" whose consumption behavior is disassociated from that of the other 90% of their country's population.

Whether there is evidence of divergence or not hinges on whether one restricts one's attention to the early part of the diffusion process. What holds for one stage need not hold for another. How various correlates and causal mechanisms map differently into early versus late stages of the diffusion process warrants more research (Stremersch and Tellis 2004).

Our findings of divergence in the speed to 50% but not 10% raise the possibility that the "flattening" forces of improved infrastructure, improved communication and increased homogenization have as yet been more pronounced in the top 10% than the top 50% of the population. Sound, direct evidence of within-county variation in the degree of globalization and world-flattening would be very valuable for practitioners seeking a nuanced and actionable understanding of where the most attractive growth opportunities lie.

Income growth and diffusion speed: Product contingencies. White goods diffuse differently than other consumer durables. Specifically, their diffusion speed within a country is less boosted by income growth within that country than the diffusion speed of other goods is. That the diffusion of more necessity-like and less visible white goods is less boosted by income gains than the diffusion of other products is to be expected (Bonus 1973).

What is less expected is that when one jointly considers the main and interaction effects in Tables 5 and 8, income gains do not appear to matter at all or may even decelerate the diffusion of white goods. One possible explanation is that people like to display their new wealth through more visible consumer electronics and telecom products instead (compare Heffetz 2011). Another explanation might be that improved purchasing power is matched by quality and price increases (e.g., more expensive, larger refrigerators with brushed steel finishing), so the rate of diffusion does not change markedly. There may be other forces at work, like the use of rent-to-own financing plans by low-income consumers. Finally, it is also possible that the effect of income growth is better represented as expanding the "population at risk" or diffusion ceiling rather than increasing the speed of diffusion within a population of static size (Dekimpe, Parker and Sarvary 1998). Future research will hopefully add some resolution to this novel finding.

Acceleration. Finally, we provide new, broad-based evidence that new product diffusion has accelerated. Our work extends prior findings of Bayus (1992) and Van den Bulte (2000) by documenting that the pattern holds (i) outside the US, (ii) for the last four decades, and (iii) after controlling for any unobserved product differences possibly associated with the time period during which the products diffused. More surprisingly, (iv) after controlling for unobserved product differences, the acceleration is more pronounced in the time to reach 50% than 10% penetration.

Implications for managers

The findings have four implications for managers assessing and quantifying growth opportunities across the globe:

- Be wary of broad-brush generalizations and starry-eyed manifestoes about the extent and speed of globalization of consumer markets.
- Be wary of forecasting how quickly a new product category will gain market traction in poor countries based on its speed of growth in rich countries. You need to consider differences across target segments and across categories.

- Such generalization may be safe if you target only the top 10% of the population, but is likely to be very misleading of you target the median household. Exercise greater patience and make larger downward adjustments in your penetration forecasts for poor vs. rich countries if your business aims to reach beyond the upper strata into the middle and the second half of the income pyramid.
- When targeting markets experiencing strong growth in income per capita, be mindful of differences between home appliances versus consumer electronics and telecom products. Growing income is associated with increased penetration growth for electronics and telecom, but not for home appliances.

References

Abel, Andrew B. and Ben S. Bernanke (2005), *Macroeconomics*. *5th ed.* Boston, MA, Addison-Wesley.

Agarwal, Rajshree and Barry L. Bayus (2002), "The Market Evolution and Sales Takeoff of Product Innovations," *Management Science*, 48, 1024–1041.

Ai, Chunrong and Edward C. Norton (2003), "Interaction Terms in Logit and Probit Models," *Economic Letters*, 80, 123-129.

Angrist, Joshua D. and Jörn-Steffen Pischke (2009), *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, Princeton, NJ.

Bayus, Barry L. (1992), "Have Diffusion Rates Been Accelerating over Time?" *Marketing Letters*, 3, 215-226

Berry, Heather, Mauro F. Guillén and Arun S. Hendi (2014), "Is there Convergence across Countries? A Spatial Approach," *Journal of International Business Studies,* 45, 387-404.

Berry, William D., Jacqueline H.R. DeMeritt and Justin Esarey, (2010), "Testing for Interaction in Binary Logit and Probit Models: Is a Product Term Essential?" *American Journal of Political Science*, 54 (1), 248-266.

Bonus, Holger (1973), "Quasi-Engel Curves, Diffusion, and the Ownership of Major Consumer Durables", *Journal of Political Economy*, 81, 655-677.

Chandrasekaran, Deepa and Gerard J. Tellis (2007), "A Critical Review of Marketing Research on Diffusion of New Products," *Review of Marketing Research,* 3, 39-80.

____ and ____ (2008), "Global Takeoff of New Products: Culture, Wealth or Vanishing Differences," *Marketing Science,* 27 (5), 844-860.

Cheung, Yin B. (2007), "A Modified Least Squares Regression Approach to the Estimation of Risk Difference," *American Journal of Epidemiology*, 166, 1337-1344.

Comin, Diego A. and Bart Hobijn (2010), "An Exploration of Technology Diffusion," *American Economic Review*, 100 (5), 2031-59.

____ and Martí Mestieri Ferrer (2013), "If technology has arrived everywhere, why has income diverged?" Working Paper No 19010, National Bureau of Economic Research, Cambridge, MA.

Cox, W. Michael and Richard Alm (1996), "The economy at light speed: Technology and growth in the information age and beyond," In *Federal Reserve Bank of Dallas 1996 Annual Report*, Dallas, TX, 2-17.

Dekimpe, Marnik G., Philip M. Parker, and Miklos Sarvary (1998), "Staged Estimation of International Diffusion Models: An Application to Global Cellular Telephone Adoption," *Technological Forecasting and Social Change*, 57 (1), 105-132.

____, ____ and ____ (2000), “Multimarket and Global Diffusion,” In *New-Product Diffusion Models*. V. Mahajan, E. Muller, Y. Wind. eds. Kluwer Academic Publishers, Boston, MA, 49-73.

Edwards, Ward, Harold Lindman, and Leonard J. Savage (1963), “Bayesian Statistical Inference for Psychological Research,” *Psychological Review*, 70 (3), 193-242.

Freeland, Chrystia (2011), “The Rise of the New Global Elite,” *The Atlantic*, 307 (1), 44-55.

Friedman, Thomas L. (2005), *The World Is Flat: A Brief History of the Twenty-first Century*. Farrar, Straus and Giroux, New York, NY.

Gatignon, Hubert, Jehoshua Eliashberg, and Thomas S. Robertson (1989), “Modeling Multinational Diffusion Patterns: An Efficient Methodology,” *Marketing Science*, 8 (3), 231-247.

Gelper, Sarah and Stefan Stremersch (2014), “Variable Selection in International Diffusion Models,” *International Journal of Research in Marketing*, 31 (4), 356-367.

Getz, Malcolm, John J. Siegfried and Kathryn H. Anderson (1997), “Adoption of Innovations in Higher Education,” *Quarterly Review of Economics and Finance*, 37 (3), 605–631.

Greenland, Sander and Kenneth J. Rothman (1998), *Modern Epidemiology*. *2nd ed.* Philadelphia, PA: Lippincott-Raven Publishers.

Griliches, Zvi (1957), “Hybrid Corn: An Exploration in the Economics of Technological Change,” *Econometrica,* 25 (4), 501–522.

Hartman, Brian M., Bani K. Mallick, and Debabrata Talukdar (2012), “Investigating International New Product Diffusion Speed: A Semiparametric Approach,” *Annals of Applied Statistics*, 6 (2), 625-651.

Heffetz, Ori (2011), “A Test of Conspicuous Consumption: Visibility and Income Elasticities,” *Review of Economics and Statistics*, 93 (4), 1101-1117.

Hernandez, Lyla M. and Dan G. Blazer. (2006), *Committee on Assessing Interactions among Social, Behavioral, and Genetic Factors in Health,* Washington (DC): National Academies Press.

Heston, Alan, Robert Summers and Bettina Aten (2012), “Penn World Table Version 7.1.” Center for International Comparisons of Production, Income and Prices, University of Pennsylvania, Philadelphia, PA.

Hu, Yansong and Christophe Van den Bulte (2014), “Nonmonotonic Status Effects in New Product Adoption,” *Marketing Science*, 33 (4), 509-533.

Irwin, Julie R. and Gary H. McClelland (2003), “Misleading Heuristics and Moderated Multiple Regression Models,” *Journal of Marketing Research*, 48 (1), 100-109.

Iyengar, Raghuram, Christophe Van den Bulte and Thomas W. Valente (2011), "Opinion Leadership and Social Contagion in New Product Diffusion," *Marketing Science,* 30 (2), 195–212.

____, ____ and Jae Y. Lee (2015), "Social Contagion in New Product Trial and Repeat," *Marketing Science*, 34 (3), 408-429.

Jiang, Zhengrui, Frank M. Bass and Portia Isaacson Bass (2006), "Virtual Bass Model and the Left-hand Data-truncation Bias in Diffusion of Innovation Studies," *International Journal of Research in Marketing*, 23 (1), 93–106.

Jomo, Kwame S. and Jacques Baudot, eds (2007), *Flat World, Big Gaps: Economic Liberalization, Globalization, Poverty & Inequality*, United Nations, New York, NY.

Keegan, Warren J. and Mark C. Green (2012), *Global Marketing*, *7th ed.* Prentice-Hall, Upper Saddle River, NJ.

Knol, Mirjam J., Matthias Egger, Pippa Scott, Mirjam I. Geerlings, and Jan P. Vandenbroucke (2009), "When One Depends on the Other: Reporting of Interaction in Case-control and Cohort Studies," *Epidemiology,* 20 (2), 161-6.

Levitt, Theodore (1983), "The Globalization of Markets," *Harvard Business Review*. 61 (3), 92-102.

Lilien, Gary L., Arvind Rangaswamy and Christophe Van den Bulte (2000), "Diffusion Models: Managerial Applications and Software," in *New-Product Diffusion Models*, V. Mahajan, E. Muller and Y. Wind, eds., Boston, MA: Kluwer Academic Publishers, 295-336.

Lim, Byeong-Lak, Munkee Choi and Myeong-Cheol Park (2003), "The Late Take-off Phenomenon in the Diffusion of Telecommunication Services: Network Effect and the Critical Mass," *Information Economics and Policy* **15** (4), 537-557.

Mankiw, N. Gregory, David Romer and David N. Weil (1992), "A Contribution to the Empirics of Economic Growth," *Quarterly Journal of Economics*, 107 (2), 407-437.

Milanovic, Branko (2013), "Global Income Inequality in Numbers: In History and Now," *Global Policy*, 4 (2), 198-208.

____ (2015), "Global Inequality of Opportunity: How Much of our Income is Determined by where We Live?" *Review of Economics and Statistics*, 97 (2), 452-460.

Nieto F. Javier and Moyses Szklo (2000), *Epidemiology: Beyond the Basics*, Sudbury, MA: Jones and Bartlett.

Peres, Renana, Eitan Muller and Vijay Mahajan (2010), "Innovation Diffusion and New Product Growth Models: A Critical Review and Research Directions," *International Journal of Research in Marketing*, 27, 91–106.

Rothman, Kenneth J., Sander Greenland, and Alexander M. Walker (1980), "Concepts of Interaction," *American Journal of Epidemiology*, 112, 467– 470.

Russell, Thomas (1980), "Comments on the Relationship between Diffusion Rates, Experience Curves, and Demand Elasticities for Consumer Durable Technological Innovations," *Journal of Business*, 53 (3), S69-S73.

Sachs, Jeffrey D. and Andrew Warner (1995), "Economic Reform and the Process of Global Integration," *Brookings Papers on Economic Activity*, 1, 1-95.

Sala-i-Martin, Xavier X. (1996), "The Classical Approach to Convergence Analysis," *Economic Journal*, 106 (July), 1019-1036.

Sood, Ashish, Gareth James, and Gerard J. Tellis (2009), "Functional Regression: A New model for Predicting Market Penetration of New Products," *Marketing Science*, 28, 36-51.

Stremersch, Stefan and Gerard J. Tellis (2004), "Understanding and Managing International Growth of New Products," *International Journal of Research in Marketing*, 21, 421-438.

Tellis, Gerard J., Stefan Stremersch, and Eden Yin (2003), "The International Takeoff of New Products: The Role of Economics, Culture, and Country Innovativeness," *Marketing Science*, 22, 188–208.

Vandenbroucke Jan P., Erik von Elm, Douglas G. Altman, et al (2007), "Strengthening the Reporting of Observational Studies in Epidemiology (STROBE): Explanation and Elaboration," *PLoS Medicine*. 4, e297.

Van den Bulte, Christophe (2000), "New Product Diffusion Acceleration: Measurement and Analysis," *Marketing Science*, 19, 366–380.

____ (2004), "Multigeneration Innovation Diffusion and Intergeneration Time: A Cautionary Note," *Journal of the Academy of Marketing Science,* 32 (3), 357-360.

____ and Raghuram Iyengar (2011), "Tricked by Truncation: Spurious Duration Dependence and Social Contagion in Hazard Models," *Marketing Science,* 30 (2), 233-248.

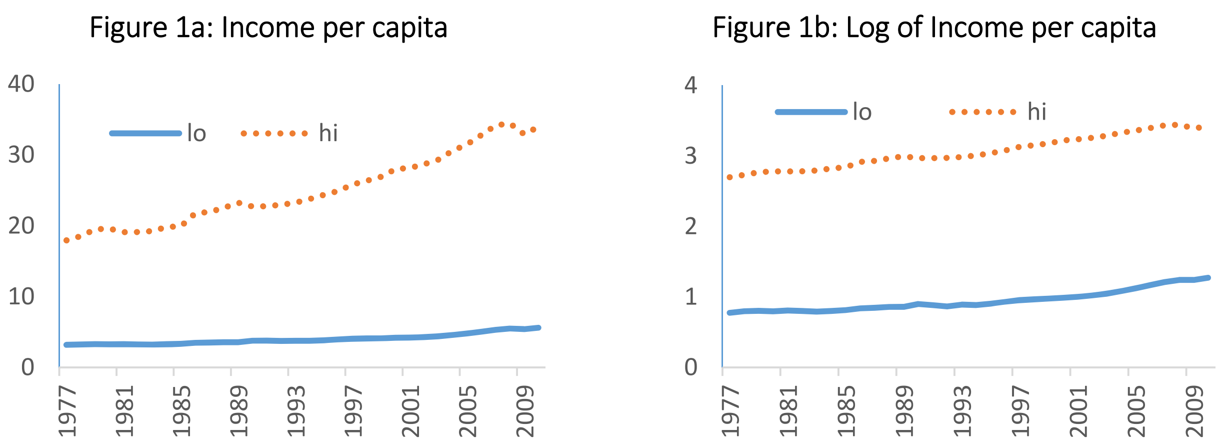
____ and Gary L. Lilien (1997), "Bias and Systematic Change in the Parameter Estimates of Macro-level Diffusion Models," *Marketing Science*, 16 (4), 338-353.

____ and Stefan Stremersch (2004), "Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta-analytic Test," *Marketing Science*, 23, 530–544.

Van Everdingen, Yvonne, Dennis Fok, and Stefan Stremersch (2009), "Modeling Global Spillover of New Product Takeoff," *Journal of Marketing Research*, 46 (5) 637-652.

Wooldridge, Jeffrey M. (2002), *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Figure 1: Evolution of Income per Capita for High- and Low-Income Countries (1977-2010)



Income per capita is measured as PPP (purchasing power parity) converted GDP per capita ($ 000) at 2005 constant prices (variable *rgdpch* in Penn World Table version 7.1). The high-income group includes Taiwan and 51 countries classified in 2012 by the World Bank as high-income countries; the low-income group includes 137 countries classified in 2012 by the World Bank as low- or middle-income countries. Together, the two groups include all countries for which the Penn World Table (7.1) reports income in PPP dollars.

Figure 2: Empirical Hazard Rates of Reaching 10% (Full and GT10 data)

Full

Figure 2a: Hazards for 10% Penetration against Calendar Time (Full)

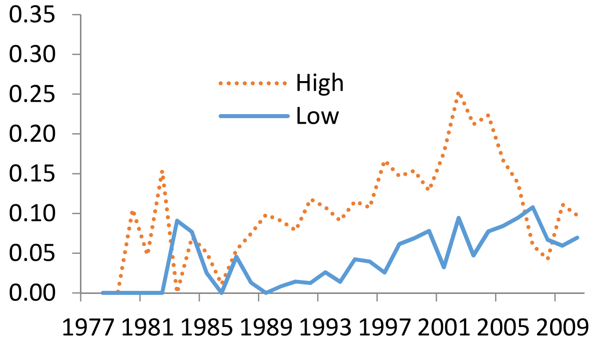


Figure 2b: Hazards for 10% Penetration against Vintage

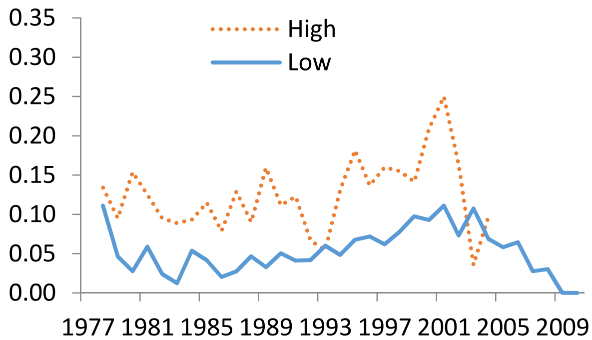
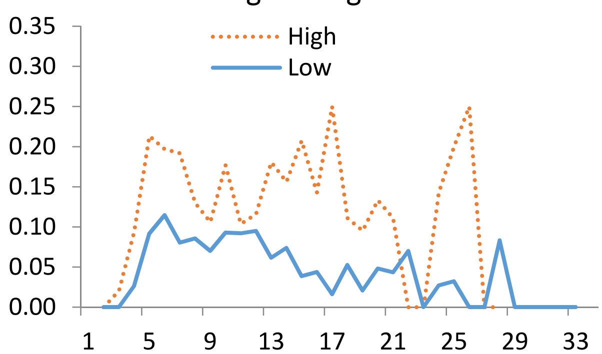


Figure 2c: Hazards for 10% Penetration against Age



GT10

Figure 2d: Hazards for 10% Penetration against Calendar Time

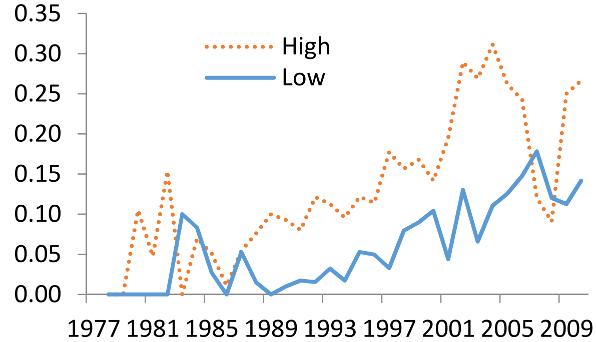


Figure 2e: Hazards for 10% Penetration against Vintage

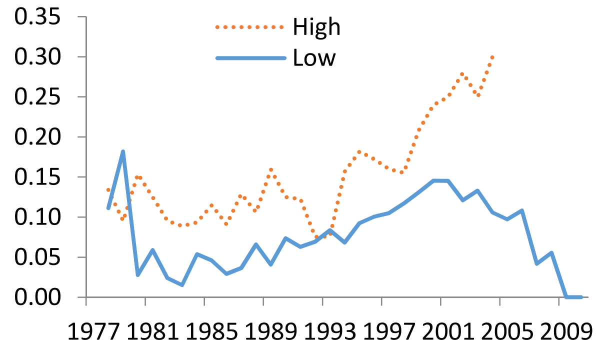


Figure 2f: Hazards for 10% Penetration against Age

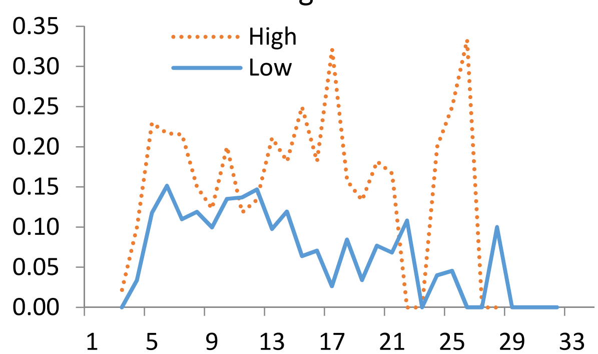


Figure 3: Empirical Hazard Rates of Reaching 50% Full and GT50 data)

Full

Figure 3a: Hazards for 50% Penetration against Calendar Time

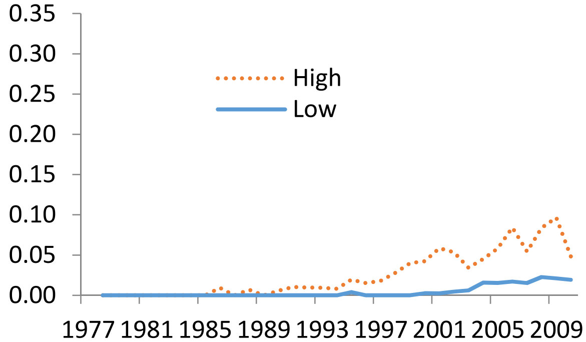


Figure 3b: Hazards for 50% Penetration against Vintage

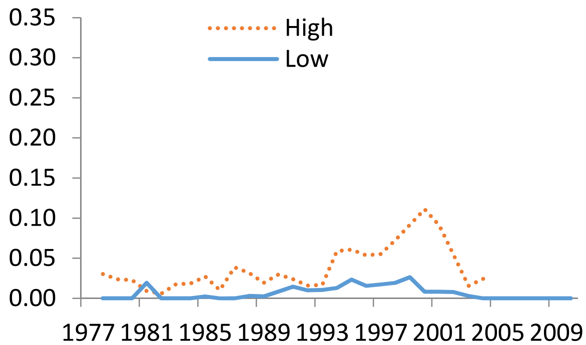
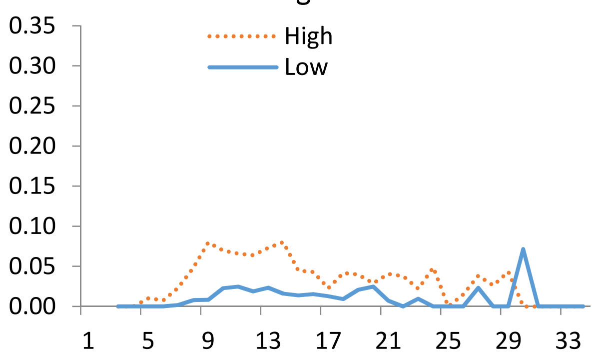


Figure 3c: Hazards for 50% Penetration against Age



GT10

Figure 3d: Hazards for 50% Penetration against Calendar Time

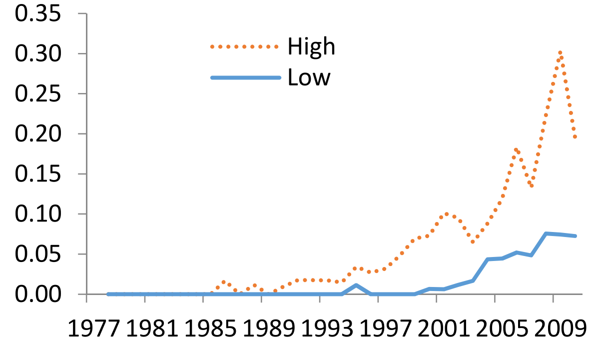


Figure 3e: Hazards for 50% Penetration against Vintage

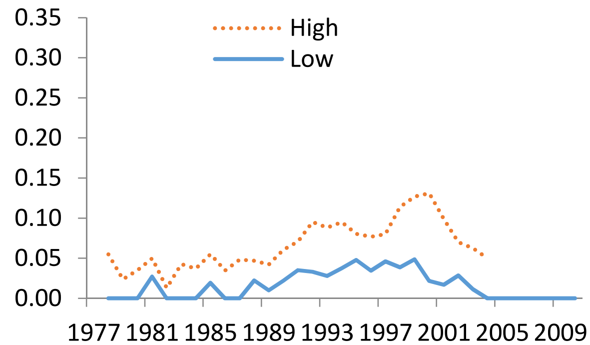


Figure 3f: Hazards for 50% Penetration against Age

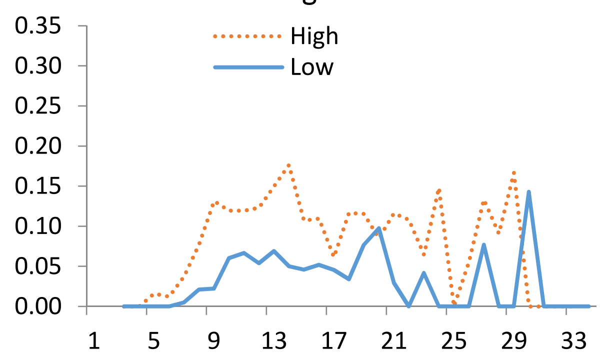
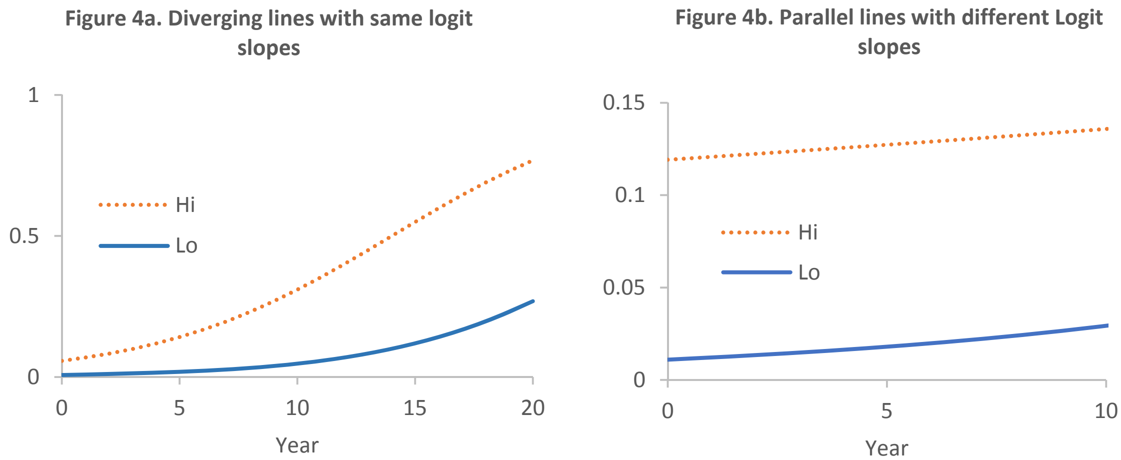


Figure 4. Examples of inconsistency between divergence in linear and log-odds space



The lines in (5a) are logistic curves with the same slope coefficient or shape parameter but a different intercept or location parameter. Hi: $\ln\{h_t/(1-h_t)\} = -2.8 + 0.2\times Year_t$; Lo: $\ln\{h_t/(1-h_t)\} = -5 + 0.2\times Year_t$. The lines in (5b) are logistic curves with different slopes coefficients or shape parameters and different intercepts or location parameters. Hi: $\ln\{h_t/(1-h_t)\} = -2 + 0.015\times Year_t$; Lo: $\ln\{h_t/(1-h_t)\} = -4.5 + 0.100 \times Year_t$.

Table 1: Countries and Products Included in the Analysis

38 rich countries	Australia, Austria, Bahrain, Belgium, Canada, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Ireland, Israel, Italy, Japan, Kuwait, Netherlands, New Zealand, Norway, Poland, Portugal, Qatar, Saudi Arabia, Singapore, Slovakia, Slovenia , South Korea, Spain, Sweden, Switzerland, Taiwan, United Arab Emirates, USA, United Kingdom
48 poor countries	Algeria, Argentina, Azerbaijan, Belarus, Bolivia, Bosnia-Herzegovina, Brazil, Bulgaria, Cameroon, Chile, China, Colombia, Costa Rica, Dominican Republic, Ecuador, Egypt, Georgia, Guatemala, India, Indonesia, Iran, Jordan, Kazakhstan, Kenya, Latvia, Lithuania, Macedonia, Malaysia, Mexico, Montenegro, Morocco, Nigeria, Pakistan, Peru, Philippines, Romania, Russia, Serbia, South Africa, Thailand, Tunisia, Turkey, Turkmenistan, Ukraine, Uruguay, Uzbekistan, Venezuela, Vietnam
15 Products	Air Conditioner, Broadband Internet Enabled Computer, CD Player, Cable TV, DVD Player/Recorder, Dishwasher, Internet Enabled Computer, Microwave Oven, Mobile Telephone, Personal Computer, Satellite TV System, Tumble Drier, Video Camera, Video Game Console, Videotape Recorder

Table 2. Products and product-country combinations included in the study

	Full		GT10		GT50	
Category	***N***	**%hi**	***N***	**%hi**	***N***	**%hi**
Air Conditioner	66	36%	38	34%	7	43%
Broadband Internet Enabled Computer	73	42%	72	42%	48	65%
CD Player	56	45%	42	57%	17	88%
Cable TV	52	38%	48	35%	26	42%
DVD Player/Recorder	78	41%	74	42%	46	70%
Dishwasher	47	26%	22	50%	5	80%
Internet Enabled Computer	76	39%	71	41%	59	51%
Microwave Oven	56	21%	49	24%	22	55%
Mobile Telephone	74	42%	72	42%	70	44%
Personal Computer	56	18%	55	18%	37	27%
Satellite TV System	67	43%	51	53%	18	50%
Tumble Drier	31	32%	15	40%	7	29%
Video Camera	42	55%	31	68%	4	50%
Video Game Console	47	47%	31	61%	3	100%
Videotape Recorder	27	22%	22	27%	12	50%
Total	848	37%	693	42%	381	56%

%hi = Percentage of observations stemming from high-income countries

Table 3: Speed to 10% in Rich vs. Poor Countries (Simple models)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	.0040***	.0056***	-.0013	.1411***	.1728***	.0069
	(.0006)	(.0006)	(.0008)	(.0148)	(.0160)	(.0203)
Year × Hi	.0008	.0083***	-.0013	-.0438*	.0747**	-.0519*
	(.0015)	(.0019)	(.0018)	(.0202)	(.0237)	(.0238)
Vintage		-.0064***			-.1413***	
		(.0008)			(.0187)	
Vintage × Hi		-.0106***			-.1496***	
		(.0020)			(.0217)	
Age			.0240***			.7445***
			(.0017)			(.0623)
Age × Hi			.0229***			.1412
			(.0045)			(.0826)
Age^2			-.0008***			-.0268***
			(.0001)			(.0029)
Age^2 × Hi			-.0009***			-.0027
			(.0003)			(.0044)
R2	.080	.096	.116			
-2LL				3,569.7	3,388.9	3,156.5

* *p* <. 05; ** *p* <. 01; *** *p* <. 001. Standard errors in parentheses. All models are estimated on 15 products, 78 countries, and 848 combinations. All models include product and country dummies. Hi does not enter as a main effect because it is absorbed by the country dummies.

Table 4: Speed to 10% in Rich vs. Poor Countries (Richer Models)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
D2000	-.1339*	-.1696**	-.2270***	-.2406	-.8123	-.1887
	(.0598)	(.0618)	(.0616)	(1.1536)	(1.2405)	(1.257)
D2000 × Inc2000	1.6100*	1.7672**	1.8731**	23.8521***	25.8721***	24.3313**
	(.6268)	(.6692)	(.6577)	(7.2003)	(7.8752)	(8.1037)
Year_pre	.0019	.0036*	-.0039**	.1464***	.2600***	.0266
	(.0012)	(.0017)	(.0013)	(.0398)	(.0490)	(.0443)
Year_post	.0076***	.0086***	.0054*	.1588***	.1844***	.0366
	(.0020)	(.0019)	(.0022)	(.0306)	(.0318)	(.0375)
Year_pre × Inc2000	.0135	.0874***	.0041	-.1903	.6613***	-.2381
	(.0077)	(.0132)	(.0075)	(.1418)	(.2054)	(.1601)
Year_post × Inc2000	-.0304	-.0176	-.0481*	-.2982	.0264	-.3125
	(.0198)	(.0195)	(.0222)	(.2030)	(.2114)	(.2423)
R2	.079	.108	.119			
-2LL				3,575.6	3,293.5	3,153.3

* *p* <. 05; ** *p* <. 01; *** *p* <. 001. Standard errors in parentheses. All models are estimated on 15 products, 78 countries, and 848 combinations. All models include product and country dummies. Hi does not enter as a main effect because it is absorbed by the country dummies. Models (2) and (5) also include Vintage, Vintage × Inc2000, D2000 × Vintage, and D2000 × Vintage × Inc2000, whereas Models (3) and (6) also include Age, Age × Inc2000, Age^2, and Age^2 × Inc2000. All coefficients and standards errors involving Inc2000 are inflated by a factor of 100 to avoid reporting very small values.

Table 5: Speed to 10% in Rich vs. Poor Countries (Models with Income)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
D2000	-.0998	-.1423*	-.1990**	-.0455	-.9053	-.0066
	(.0617)	(.0636)	(.0648)	(1.1864)	(1.2603)	(1.2778)
D2000 × Inc2000	1.8400**	2.0047**	2.0237**	33.0838***	38.5665***	33.6355***
	(.6158)	(.6572)	(.6375)	(8.5760)	(9.2769)	(9.4434)
Year_pre	.0025*	.0035*	-.0033*	.1533***	.2487***	.0263
	(.0012)	(.0017)	(.0013)	(.0400)	(.0490)	(.0448)
Year_post	.0067***	.0076***	.0048*	.1564***	.1806***	.02940
	(.0020)	(.0020)	(.0022)	(.0314)	(.0327)	(.0375)
Year_pre × Inc2000	.0015	.0788***	-.0055	-.3053*	.5909**	-.3841*
	(.0096)	(.0144)	(.0096)	(.1524)	(.2110)	(.1708)
Year_post × Inc2000	-.0335	-.0228	-.0532*	-.3894	-.1642	-.5225*
	(.0195)	(.0194)	(.0213)	(.2190)	(.2255)	(.2545)
IncDiff	.7007*	.5480	.5007	6.7990*	7.0956*	8.0559*
	(.3043)	(.3006)	(.3253)	(3.1298)	(3.3280)	(3.3796)
IncDiff × WG	-.4527*	-.1258	-.1157	-5.3185	4.4683	3.1541
	(.2144)	(.2106)	(.2145)	(3.5673)	(4.3806)	(4.4101)
Gini	.0669	.0514	.0199	3.4615*	3.7710*	2.6115
	(.0730)	(.0723)	(.0715)	(1.7495)	(1.8179)	(1.8731)
Gini × WG	.1761**	.1173	.1189	2.1805	-.0010	.6075
	(.0610)	(.0611)	(.0612)	(1.4038)	(1.5192)	(1.5605)
R2	.081	.109	.119			
-2LL				3,562.1	3,282.5	3,144.4

* *p* <. 05; ** *p* <. 01; *** *p* <. 001. Standard errors in parentheses. All models are estimated on 15 products, 78 countries, and 848 combinations. All models include product and country dummies. Hi does not enter as a main effect because it is absorbed by the country dummies. Models (2) and (5) also include Vintage, Vintage × Inc2000, D2000 × Vintage, and D2000 × Vintage × Inc2000, whereas Models (3) and (6) also include Age, Age × Inc2000, Age^2, and Age^2 × Inc2000. All coefficients and standards errors involving Inc2000 or IncDiff are inflated by a factor of 100 to avoid reporting very small values.

Table 6: Speed to 50% in Rich vs. Poor Countries (Simple models)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	.0007*	.0013***	-.0012***	.3718***	.3781***	.1574**
	(.0003)	(.0003)	(.0003)	(.0451)	(.0455)	(.0550)
Year × Hi	.0017*	.0010	.0028***	-.0291	-.0159	-.0151
	(.0006)	(.0006)	(.0008)	(.0475)	(.0487)	(.0523)
Vintage		-.0022***			-.147***	
		(.0003)			(.0396)	
Vintage × Hi		.0017**			-.0131	
		(.0006)			(.0348)	
Age			.005***			1.0055***
			(.0007)			(.1567)
Age × Hi			.0057***			-.101
			(.0012)			(.1691)
Age^2			-.0001***			-.0283***
			(0)			(.0053)
Age^2 × Hi			-.0003***			.0035
			(.0001)			(.0061)
R2	.063	.066	.075			
-2LL				1,530.1	1,495.2	1,368.9

* *p* <. 05; ** *p* <. 01; *** *p* <. 001. Standard errors in parentheses. All models are estimated on 15 products, 78 countries, and 848 combinations. All models include product and country dummies. Hi does not enter as a main effect because it is absorbed by the country dummies.

Table 7: Speed to 10% in Rich vs. Poor Countries (Richer Models)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
D2000	-.0793***	-.0752***	-.0772***	-7.2874	-11.2056*	-7.6311
	(.0161)	(.0160)	(.0164)	(5.3948)	(5.5523)	(5.9171)
D2000 × Hi	.0246	-.0384	-.1319*	6.3523*	5.9894*	5.7897*
	(.0535)	(.0594)	(.0633)	(2.4714)	(2.5853)	(2.8348)
Year_pre	-.0008***	.0000	-.0025***	-.0123	.2200	-.2551
	(.0002)	(.0002)	(.0003)	(.2649)	(.2570)	(.2955)
Year_post	.0025***	.0030***	.0006	.3774***	.4432***	.1545*
	(.0006)	(.0006)	(.0006)	(.0528)	(.0566)	(.0632)
Year_pre × Hi	.0009	.0026**	.0006	.2269	.1318	.1822
	(.0007)	(.0009)	(.0007)	(.2719)	(.2651)	(.2993)
Year_post × Hi	.0010	.0007	.0057**	-.0691	-.0974	-.0427
	(.0018)	(.0017)	(.0022)	(.0608)	(.0632)	(.0675)
R2	.066	.074	.082			
-2LL				1,518.1	1,425.0	1,350.8

* *p* <. 05; ** *p* <. 01; *** *p* <. 001. Standard errors in parentheses. All models are estimated on 15 products, 78 countries, and 848 combinations. All models include product and country dummies. Hi does not enter as a main effect because it is absorbed by the country dummies. Models (2) and (5) also include Vintage, Vintage × Hi, D2000 × Vintage, and D2000 × Vintage × Hi, whereas Models (3) and (6) also include Age, Age × Hi, Age^2, and Age^2 × Hi.

Table 8 Speed to 10% in Rich vs. Poor Countries (Models with Income)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
D2000	-.0966***	-.0826**	-.0701**	-9.6203*	-13.2832**	-1.6378*
	(.0256)	(.0263)	(.0265)	(4.5908)	(4.7815)	(4.8738)
D2000 × Inc2000	.4300	.1016	-.3543	49.8095***	48.0336**	44.0806**
	(.2487)	(.2833)	(.2984)	(15.3565)	(15.7556)	(16.7404)
Year_pre	-.0009*	-.0009	-.0026***	-.1059	.2410	-.3527
	(.0004)	(.0006)	(.0005)	(.2093)	(.2209)	(.2252)
Year_post	.0029***	.0036***	.0000	.4147***	.5050***	.1909**
	(.0009)	(.0008)	(.0010)	(.0567)	(.0624)	(.0672)
Year_pre × Inc2000	.0034	.0134**	.0033	.9683	.3285	.8598
	(.0037)	(.0046)	(.0036)	(.6664)	(.7080)	(.7124)
Year_post × Inc2000	-.0013	.0004	.0237*	-.5098*	-.6431*	-.3734
	(.0071)	(.0072)	(.0096)	(.2499)	(.2629)	(.2845)
IncDiff	.3275*	.2441	.2119	6.1960*	5.4048	7.4006*
	(.1453)	(.1420)	(.1413)	(2.8844)	(3.0169)	(3.2061)
IncDiff × WG	-.4255***	-.4096***	-.4413***	-21.0255**	-11.1483	-11.5955
	(.1005)	(.1021)	(.1046)	(6.9030)	(8.3063)	(7.9252)
Gini	.0143	.0074	.0003	1.4040	.1151	-.4183
	(.0235)	(.0236)	(.0234)	(4.6903)	(4.7855)	(4.7921)
Gini × WG	.0589**	.0570*	.0408	-1.7594	-3.4074	-1.3528
	(.0216)	(.0228)	(.0219)	(3.5947)	(3.8745)	(3.7376)
R-Square	.065	.075	.082			
-2LL				1,512.4	1,419.2	1,347.8

* p <. 05; ** p <. 01; *** p <. 001. Standard errors in parentheses. All models are estimated on 15 products, 78 countries, and 848 combinations. All models include product and country dummies. Inc2000 does not enter as a main effect because it is absorbed by the country dummies. Models (2) and (5) also include Vintage, Vintage × Inc2000, D2000 × Vintage, and D2000 × Vintage × Inc2000, whereas Models (3) and (6) also include Age, Age × Inc2000, Age^2, and Age^2 × Inc2000. All coefficients and standards errors involving Inc2000 or IncDiff are inflated by a factor of 100 to avoid reporting very small values.

Appendix

1. Income evolution among countries studied

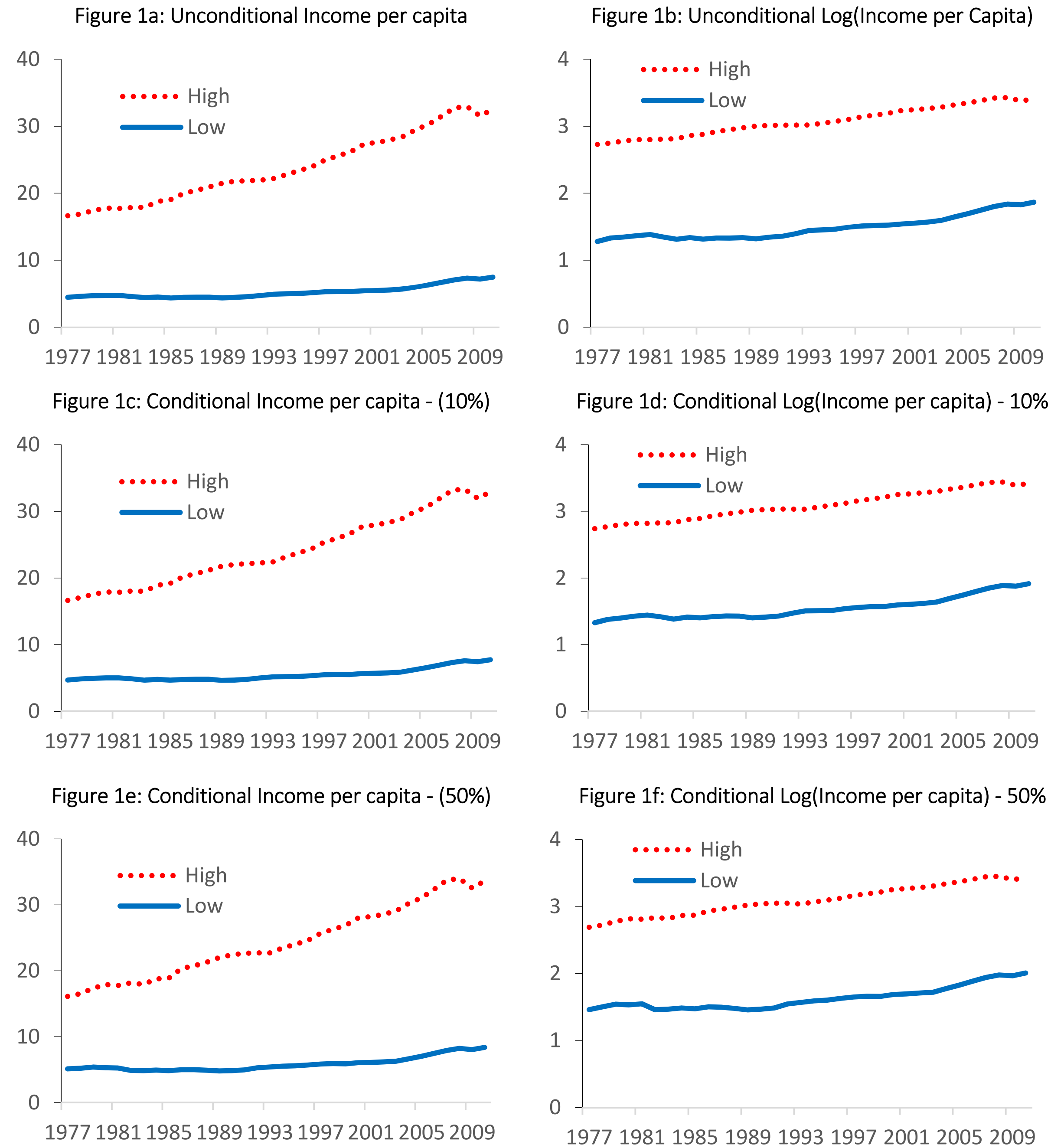
Figures WA-1a and Wa-1b show how the average income per capita has evolved from 1977 to 2010 for the 86 countries we analyze. The patterns are extremely similar to those in Figure 1 for all 189 countries. Figure WA-1a shows that there has been a pronounced divergence in income levels from 1977 to the great recession of 2008, when growth stalled everywhere. Figure Wa-1b shows that the proportional gap in income, corresponding to the distance between the two lines of log of income, has narrowed since 2000. Yet, the gap has remained quite large, both in absolute and relative terms. The one notable difference between Figures 1 and WA-1a/b is that line for low-income countries in Figure WA-1b is somewhat higher than that in Figure 1b. The reason is that we do not have penetration data from the very poorest countries in the world.

The conditional-10% and conditional-50% data sets (Figures WA-1c, 1d, 1e, 1f) exhibit the same patterns. They exhibit income divergence and a higher income level for low income in countries than in the full population of countries.

2. Statistical analyses on GT10 and GT50 data sets

Tables WA-1 through WA-3 report the results of estimating the same models as in Tables 3-5, but estimated on the GT10 data set rather than the Full data set. Tables WA-4 through WA-6 report the results of estimating the same models as in Tables 6-8, but estimated on the GT50 data set rather than the Full data set.

Figure WA-1: Evolution of Income per Capita for High- and Low-Income Countries



Income per capita is measured as PPP (purchasing power parity) converted GDP per capita ($ 000) at 2005 constant prices (variable *rgdpch* in Penn World Table version 7.1). All high-income groups include Taiwan and 37 countries classified in 2012 by the World Bank as high-income countries. Unconditional low-income group and conditional low-income group of 10% include 48 countries classified in 2012 by the World Bank as low- or middle-income countries. Conditional low-income group of 50% include 45 countries and exclude Georgia, Turkmenistan, and Ukraine.

Table WA-1: Speed to 10% in Rich vs. Poor Countries (Simple models; GT10)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	.0072***	.0088***	-.0004	.1756***	.1989***	.0514*
	(.0008)	(.0009)	(.0012)	(.0158)	(.0169)	(.0212)
Year × Hi	.0014	.0097***	-.0008	-.0389	.0798**	-.0474
	(.0019)	(.0023)	(.0022)	(.0216)	(.0258)	(.0249)
Vintage		-.0085***			-.1273***	
		(.0013)			(.0192)	
Vintage × Hi		-.0113***			-.1501***	
		(.0023)			(.0225)	
Age			.0338***			.7333***
			(.0024)			(.0629)
Age × Hi			.0181***			.1023
			(.0053)			(.0845)
Age^2			-.0011***			-.0267***
			(.0001)			(.0029)
Age^2 × Hi			-.0007***			-.0014
			(.0003)			(.0045)
R-Square	.081	.097	.122			
-2LL				3,294.1	3,157.5	2,937.2

* *p* <. 05; ** *p* <. 01; *** *p* <. 001. Standard errors in parentheses. Models 1-3 (4-6) are estimated on 15 (15) products, 78 (76) countries, and 848 (693) combinations. All models include product and country dummies. Hi does not enter as a main effect because it is absorbed by the country dummies.

Table WA-2: Speed to 10% in Rich vs. Poor Countries (Richer models; GT10)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
D2000	-.2773**	-.3089***	-.3793***	-.9439	-1.6159	-.6047
	(.0924)	(.0957)	(.0963)	(1.2124)	(1.2988)	(1.3224)
D2000 × Inc2000	1.1800	.8506	.7845	21.7568**	2.1306*	16.6071
	(.8849)	(.9481)	(.9549)	(7.5582)	(8.1404)	(8.4758)
Year_pre	.0027	.0061**	-.0055**	.1659***	.2693***	.0568
	(.0015)	(.0020)	(.0017)	(.0415)	(.0508)	(.0461)
Year_post	.0143***	.0150***	.0100***	.2064***	.2262***	.0829*
	(.0032)	(.0031)	(.0036)	(.0324)	(.0334)	(.0393)
Year_pre × Inc2000	.0163	.0836***	.0097***	-.1838	.5944**	-.2584
	(.0083)	(.0140)	(.0082)	(.1471)	(.2106)	(.1648)
Year_post × Inc2000	.0031	.0171	.0110	-.0947	.2186	.0382
	(.0305)	(.0299)	(.0344)	(.2163)	(.2264)	(.2557)
R-Square	.082	.112	.129			
-2LL				3,292.1	3,066.7	2,927.5

* *p* <. 05; ** *p* <. 01; *** *p* <. 001. Standard errors in parentheses. Models 1-3 (4-6) are estimated on 15 (15) products, 78 (76) countries, and 848 (693) combinations. All models include product and country dummies. Inc2000 does not enter as a main effect because it is absorbed by the country dummies. Models (2) and (5) also include Vintage, Vintage × Inc2000, D2000 × Vintage, and D2000 × Vintage × Inc2000, whereas Models (3) and (6) also include Age, Age × Inc2000, Age^2, and Age^2 × Inc2000. All coefficients and standards errors involving Inc2000 are inflated by a factor of 100 to avoid reporting very small values.

Table WA-3: Speed to 10% in Rich vs. Poor Countries (Models with Income; GT10)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
D2000	-.0966***	-.0826**	-.0701**	-.855	-1.8288	-.6068
	(.0256)	(.0263)	(.0265)	(1.2539)	(1.3295)	(1.3463)
D2000 × Inc2000	.43	.1016	-.3543	32.618***	33.7661***	27.2803**
	(.2487)	(.2833)	(.2984)	(9.0099)	(9.6642)	(9.7998)
Year_pre	-.0009*	-.0009	-.0026***	.171***	.2577***	.0551
	(.0004)	(.0006)	(.0005)	(.0419)	(.0509)	(.0467)
Year_post	.0029***	.0036***	.0000	.2065***	.2268***	.0812*
	(.0009)	(.0008)	(.0010)	(.0334)	(.0345)	(.0394)
Year_pre × Inc2000	.0034	.0134**	.0033**	-.3013	.5424	-.3759*
	(.0037)	(.0046)	(.0036)	(.1595)	(.2176)	(.1766)
Year_post × Inc2000	-.0013	.0004	.0237	-.2444	.0139	-.2002
	(.0071)	(.0072)	(.0096)	(.2354)	(.2436)	(.2730)
IncDiff	.3275*	.2441	.2119	7.0057*	6.0019	6.5925
	(.1453)	(.142)	(.1413)	(3.3655)	(3.5587)	(3.4400)
IncDiff × WG	-.4255***	-.4096***	-.4413***	-3.4773	5.7976	3.8994
	(.1005)	(.1021)	(.1046)	(3.99)	(4.859)	(4.8239)
Gini	.0143	.0074	.0003	4.092*	4.1847*	2.9278
	(.0235)	(.0236)	(.0234)	(1.7929)	(1.8482)	(1.8848)
Gini × WG	.0589**	.057*	.0408*	.6896	-.4023	.0256
	(.0216)	(.0228)	(.0219)	(1.5482)	(1.6171)	(1.6591)
R-Square	.065	.075	.082			
-2LL				3,281.2	3,056.4	2,920.3

* *p* <. 05; ** *p* <. 01; *** *p* <. 001. Standard errors in parentheses. Models 1-3 (4-6) are estimated on 15 (15) products, 78 (76) countries, and 848 (693) combinations. All models include product and country dummies. Inc2000 does not enter as a main effect because it is absorbed by the country dummies. Models (2) and (5) also include Vintage, Vintage × Inc2000, D2000 × Vintage, and D2000 × Vintage × Inc2000, whereas Models (3) and (6) also include Age, Age × Inc2000, Age^2, and Age^2 × Inc2000. All coefficients and standards errors involving Inc2000 or IncDiff are inflated by a factor of 100 to avoid reporting very small values.

Table WA-4: Speed to 50% in Rich vs. Poor Countries (Simple models; GT50)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	.0046***	.0051***	.0001	.4651***	.4829***	.269***
	(.0008)	(.0008)	(.0010)	(.0518)	(.0535)	(.0637)
Year × Hi	.0048***	.0053***	.0048***	-.0287	-.0334	.0212
	(.0013)	(.0014)	(.0014)	(.0545)	(.0569)	(.0604)
Vintage		-.0043***			-.1592***	
		(.0010)			(.0500)	
Vintage × Hi		-.0007			.0201	
		(.0013)			(.0456)	
Age			.0099***			.9574***
			(.0019)			(.1738)
Age × Hi			.0108***			-.0633
			(.0029)			(.1911)
Age^2			-.0002***			-.0271***
			(.0001)			(.0057)
Age^2 × Hi			-.0004***			.0009
			(.0001)			(.0066)
R-Square	.095	.098	.109			
-2LL				1,302.1	1,282.1	1,178.5

* p <. 05; ** p <. 01; *** p <. 001. Standard errors in parentheses. Models 1-3 (4-6) are estimated on 15 (15) products, 78 (76) countries, and 848 (367) combinations. All models include product and country dummies. Hi does not enter as a main effect because it is absorbed by the country dummies.

Table WA-5: Speed to 50% in Rich vs. Poor Countries (Richer models; GT50)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
D2000	-.3167***	-.2944***	-.2222***	-9.6102*	-12.1968*	-1.4232
	(.0672)	(.0686)	(.0681)	(4.8497)	(5.5917)	(5.6608)
D2000 × Inc2000	-.2900	-.5910	-1.534*	34.4587**	39.6721***	29.3185*
	(.5835)	(.6231)	(.6383)	(11.4769)	(11.8131)	(13.5697)
Year_pre	-.0031**	-.0017	-.0053***	-.0326	.2887	-.2932
	(.0010)	(.0016)	(.0013)	(.2206)	(.2704)	(.2603)
Year_post	.0102***	.0108***	.0038	.4713***	.5705***	.2376***
	(.0024)	(.0024)	(.0026)	(.0602)	(.0662)	(.0711)
Year_pre × Inc2000	.0241***	.0329***	.0146**	.9961	.4154	1.1611
	(.0057)	(.0087)	(.0057)	(.6946)	(.8501)	(.8206)
Year_post × Inc2000	.0429*	.0424*	.0773***	-.1756	-.4352	.1807
	(.0194)	(.0188)	(.0216)	(.2486)	(.2637)	(.2841)
R-Square	.104	.112	.129			
-2LL				1,300.4	1,237.4	1,166.5

* *p* <. 05; ** *p* <. 01; *** *p* <. 001. Standard errors in parentheses. Models 1-3 (4-6) are estimated on 15 (15) products, 78 (76) countries, and 848 (367) combinations. All models include product and country dummies. Hi does not enter as a main effect because it is absorbed by the country dummies. Models (2) and (5) also include Vintage, Vintage × Inc2000, D2000 × Vintage, and D2000 × Vintage × Inc2000, whereas Models (3) and (6) also include Age, Age × Inc2000, Age^2, and Age^2 × Inc2000. All coefficients and standards errors involving Inc2000 are inflated by a factor of 100 to avoid reporting very small values.

Table WA-6: Speed to 50% in Rich vs. Poor Countries (Models with Income; GT50)

	Linear Models			Logit Models		
	(1)	(2)	(3)	(4)	(5)	(6)
D2000	-.3026***	-.2853***	-.2214***	-1.1964	-12.7659*	-11.3478
	(.0693)	(.0707)	(.0696)	(5.249)	(5.7452)	(5.7969)
D2000 × Inc2000	-.0200	-.3609	-1.4029*	41.2305**	43.7311**	29.6275
	(.6081)	(.6506)	(.6761)	(15.0613)	(15.3811)	(16.361)
Year_pre	-.0023*	-.0015	-.0049***	-.0314	.2959	-.2921
	(.0011)	(.0016)	(.0013)	(.2388)	(.2793)	(.266)
Year_post	.0104***	.011***	.0041	.5083***	.5952***	.2886***
	(.0024)	(.0024)	(.0026)	(.0628)	(.0685)	(.0738)
Year_pre × Inc2000	.0202**	.0311***	.0140*	.9951	.3429	1.1665
	(.0067)	(.0093)	(.0068)	(.7572)	(.8847)	(.841)
Year_post × Inc2000	.0367	.0385*	.0751***	-.4304	-.6172*	-.0691
	(.0194)	(.0192)	(.0225)	(.2826)	(.293)	(.3168)
IncDiff	.2724	.1736	.0632	5.2207	3.9044	5.3966
	(.2455)	(.2485)	(.2379)	(3.0284)	(3.1479)	(3.3826)
IncDiff × WG	-.6682**	-.5163*	-.2675	-26.069***	-19.459*	-2.0838*
	(.2199)	(.2167)	(.2187)	(7.6189)	(8.5258)	(8.0536)
Gini	.0502	.0487	.0367	-.2169	-.6976	-2.7914
	(.0842)	(.0845)	(.0853)	(4.8054)	(4.9274)	(4.9442)
Gini × WG	.1333	.0973	.0433	3.2784	1.0547	4.0254
	(.0696)	(.0733)	(.0717)	(4.497)	(4.8809)	(4.5332)
R-Square	.106	.113	.130			
-2LL				1,288.5	1,231.6	1,158.3

* p <. 05; ** p <. 01; *** p <. 001. Standard errors in parentheses. Models 1-3 (4-6) are estimated on 15 (15) products, 78 (76) countries, and 848 (367) combinations. All models include product and country dummies. Hi does not enter as a main effect because it is absorbed by the country dummies. Models (2) and (5) also include Vintage, Vintage × Inc2000, D2000 × Vintage, and D2000 × Vintage × Inc2000, whereas Models (3) and (6) also include Age, Age × Inc2000, Age^2, and Age^2 × Inc2000. All coefficients and standards errors involving Inc2000 or IncDiff are inflated by a factor of 100 to avoid reporting very small values.