Glimpsing the End of Economic History? Unconditional Convergence and the Missing Middle Income Trap

Sutirtha Roy, Martin Kessler, and Arvind Subramanian

Abstract

This paper suggests a reinterpretation of global growth—encompassing notions of unconditional convergence and the middle income trap—in the past 50 years through the lens of growth theory. We innovate by studying two modes of convergence: a classic "Solow" model where poorer countries catch up by growing faster on average; and a new "Wilde" model where catch-up growth is interpreted as growing faster than the frontier country, the United States. We apply these modes to both countries and people as units of analysis. We find that convergence has occurred faster and began earlier than widely believed. This is the case in particular after 2000, and when weighted by population We also find no evidence of a middle income trap which we defined in two ways: whether it is easier to grow and converge at lower rather than middle levels of income. The second notion is whether having reached middle income status, middle income countries find it more difficult to converge normally and become advanced countries. The last 20-30 years have thus been a golden era of convergence, challenging the new conventional wisdom of secular stagnation.

JEL Codes: O10, O15, O47

Keywords: economic growth, convergence, middle income trap

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Unconditional Convergence and the Missing Middle Income Trap

Sutirtha Roy
Office of the Chief Economic Adviser, Ministry of Finance, India

Martin Kessler
Harvard Kennedy School

Arvind Subramanian
Center for Global Development

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Center for Global Development
2055 L Street NW
Washington, DC 20036

202.416.4000
(f) 202.416.4050

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We are all in the gutter but some of us are looking at the stars.

—Oscar Wilde

I. Introduction

A pall of pessimism pervades perceptions about the world economy. Still reeling from the global financial crisis and the euro crisis and its effects, confronting the prospect of ageing, and facing uncertainty about technology-induced dynamism, the West is reluctantly reconciling to slower productivity and economic growth (Gordon, 2015). Developing countries themselves, after a heady period of rapid growth, are also in thrall to the narrative of gloom. Major emerging market countries are on a continuum between difficult transition (China) and turmoil (Brazil), and sub-Saharan Africa has been impacted by the commodity price collapse of the last two years.

But this gloom should not come in the way of recognizing that for the developing world there has been a decisive break with the past 200 years or so. This period was famously characterized by Lant Pritchett as "Divergence, Big Time" (Pritchett, 1997, Romer, 1986). Since 1820, richer countries have grown faster than poorer ones so that gaps in living standards have widened not shrunk. Even the most recent contribution by Rodrik (2014) is motivated by the stylized fact of the persistence of such divergence or disparities. This paper will document a rupture from this bleak past which we characterize as "unconditional convergence with a vengeance." Unconditional convergence occurs when, on average, poorer countries grow faster (in per capita GDP terms) than richer countries, and start catching up with standards of living in the advanced world. Today, we may be on the cusp of glimpsing—not reaching by any means—the end of economic history wherein those disparities are beginning to be durably narrowed.

The absence of convergence (until recently) had an important and perhaps unintended consequence. Triggered by the enormously influential work of Barro and Sala-i-Martin (1992), the lack of unconditional convergence led economists into what can probably, and somewhat uncharitably, be described as a massive trawling exercise in search of conditional convergence. The difference between unconditional and conditional convergence is this: the former implies that poorer countries will grow, on average, faster than richer ones; the latter implies that this will only be true if account is taken of other factors such as human capital attainment, openness and other such attributes of an economy because they determine the steady state equilibrium level of per capita GDP toward which countries converge.

Over about two decades, this exercise has spawned a major field of economics (empirical growth theory), provided livelihoods to scores of economists while sustaining economics departments in academia, and provoked lively and acrimonious debates on nearly every field of economic policy because of competing claims about what leads to conditional convergence. There is virtually no field of development economics where the dog that did not bark (unconditional convergence) has not led to vicious barking and biting in the garb of claims (on the importance of health, aid, trade, institutions, financial reform, capital account liberalization) about conditional convergence. One conjecture is that had there been unconditional convergence in the data early on, perhaps the entire discipline of empirical growth economics might have taken a different turn.

This paper makes a few contributions. First, following-up on the evidence first presented in Subramanian (2011), it will document that for the first time in recent economic history we do see unambiguous and robust evidence of unconditional convergence, prompting the claim about "glimpsing the end of economic history." In particular, in our regressions, it is the case since 1995, and even more strongly since 2005, that countries have converged. Moreover 'people' converge: when weighted by population levels, our regressions show even stronger signs of catch-up, especially after 2005. This is not just a phenomenon related to large countries, as results are robust to removing China and India.

Second, inspired by Oscar Wilde, it will advance another definition of unconditional convergence (called Wilde or W-convergence) that is both simpler and more intuitive than, and indeed complementary to, the growth economist's definition, which might be called Solow or S-convergence. S-convergence is an average concept, prevailing if on average, poorer countries grow faster than richer ones. W-convergence, on the other hand, is defined relative to the fixed point of the economic frontier, which for convenience and intuitive simplicity we adopt as the United States.

W-convergence holds simply when a country grows faster than the United States. The paper will show that to some extent the thralldom to S-convergence has in fact tended to obscure the changing fortunes and performance of poorer countries and also obscure the phenomenon of convergence which a Wilde-convergence approach helps highlight. The W-convergence complements well the usual approach because it allows to highlight and distinguish two related concepts: the *broadening* of convergence, where an increasing number of countries grow at a faster rate than the frontier; and the *acceleration* of convergence, whereby countries which are converging are doing so at a faster rate at any point in time.

Third, inspired by the work (and terminology) of Milanovic and collaborators, the paper will document W- and S-convergence for countries *and* for people. Milanovic defined three concepts of inequality: between countries; between people assuming that income distribution within a country remains unchanged; and between people accounting for changing income distribution with countries. In recent work, Milanovic (2016) showed that the between-country distribution has narrowed in the recent past—reversing more than a century and a half of divergence—while intra-country distribution of incomes has mostly widened. But since the first development has been much more quantitatively significant than the second, global inequalities have narrowed down. In the next sections, we will reframe and extend those findings through the lens of convergence theory.

If we combine, the two concepts of convergence, S and W, with the three levels at which each is measured, we have six concepts of convergence (S-1 to S-3 and W-1 to W-3) shown in the table below. Each cell then displays the precise nature of the convergence question being considered.

Six Concepts of Convergence: Solow meets Wilde

Unit/focus of Measurement	Solow (S)	Wilde (W)
1. *Country*	S-1: Are poorer *countries* catching up on average with richer ones?	W-1: Are poorer *countries* catching up with the United States?
2. *People* assuming away distributional changes within countries	S-2: Are *people* in poorer countries catching up on average with *people* in richer ones?	W-2: Are *people* in poorer countries catching up with the *average person* in the US?
3. *People* accounting for distributional changes within countries	S-3: Are *people* in poorer countries catching up on average with *people* in richer ones?	W-3: Are poorer people catching up with the *median person* in the US?

So, the first aim of this paper will be to document the remarkable change over time from divergence to unconditional convergence since the early-to-mid 1980s on all these measures of convergence.

These concepts of convergence will allow us to take on a second theme, namely the so-called middle income trap ("MIT", World Bank, 2010). A few years ago, a note of pessimism was injected into growth economics which took the form of arguing that countries that reached a certain level of income (middle income) would slow down; put differently, convergence was easier at low levels of income. The "China, 2030" report (World Bank, 2013) underlined that only 13 countries have graduated from middle to high-income status, and warned against a potential "middle income trap". In this paper, we use the simple unconditional convergence framework to analyze the middle income trap (MIT). Since there may be several interpretations to what MIT means, we specify two notions of MIT.

	Notion 1	Notion 2
Question	Are middle income countries (on average) negative outliers in an unconditional convergence framework that includes all countries?	Are middle income countries (on average) negative outliers in an unconditional convergence framework that includes only MICs and advanced countries?

The first notion asks whether there is a middle income trap generally, that is, whether growth and convergence are easier at lower levels of income than at middle levels. The second asks whether having reached a certain level of income, it is more difficult to progress beyond toward achieving advanced country status.

II. Data and Methodology

In terms of measurement and methodology, we will be computing growth rates of per capita GDP for countries and use them to (i) run unconditional convergence regressions for the S-convergence measures and; (ii) compare growth rates with that of the United States for the W-convergence measures; and (iii) run unconditional convergence regressions with appropriate middle income dummies to test for the middle income trap.

We will, however, aim at being comprehensive in three important ways: data sources, time horizons and starting points (or the base period); and for assessing the MIT, we will also be flexible in allowing a range of definitions of "middle income." It is well known that growth data vary considerably across data sources (see Johnson et al., 2013). We will compute our estimates for all three of the major data sources: the Penn World Tables (version 8, the most recent), the World Bank's World Development Indicators (WDI), and the Maddison data (most recent version). The data vary across these sources because they are estimated in different ways: in the WDI, growth data are from national income accounts, computed at constant local currency units; the growth in the PWT are based on PPP-prices (Feenstra and Inklaar, 2015); while Maddison's are based on a hybrid of PPP and national prices (in addition to the fact that Maddison makes a number of ad hoc adjustments to growth rates, for example, that of China).

Given that our third measure of convergence is a cross-country comparison of different parts of national income distributions, our analysis of S-3 and W-3 relies on income distributions data collected by the World Bank's PovcalNet and the Luxemburg Income Study (LIS) data (for details see Appendix).

Similarly in terms of the time horizons, we construct different growth rates over periods of 60, 50, 40, 30, 20, 15 and 10 years. Starting with 2015, we construct these growth rates at every five year interval up to 1950[1].

In section III, we report our estimates of Solow-1 (S-1) convergence based on the well-known convergence estimation equation of regressing the growth rates of GDP per capita on the GDP per capita of the base year. Estimates of S-2 are similarly obtained by weighing the same regression equation with the population of the given country in the base year. In S-3, we are able to test convergence across deciles of the income distribution using the PovcalNet/LIS dataset and weighing the regression with the population contained with each decile.

In section IV, we turn our attention to Wilde convergence. We report three summary statistics as part of W-convergence: (i) the proportion of developing countries that are growing faster than the United States; (ii) the average difference between the growth rates of all countries and

[1] In our sample, WDI data starts in 1980, whereas Maddison and PWT 8.0 starts in 1950. We extend our datasets to 2015 (in order to calculate the 10 year growth rates in 2005) by using IMF's latest available World Economic Outlook. (October 2014) GDP growth rate estimates. The population data is obtained from United Nations' Population Division. Countries with total population of less than 1 million and economies that are deeply dependent on oil and gas commodities are removed from the sample of all three datasets. See Appendix xx for constructing time horizons for the POVCAL and LIS datasets.

the United States; and (iii) the average difference between the growth rates of countries that are growing faster than United States and the growth rate of the US.

The intuition behind these statistics is that (i) summarizes the spread of convergence phenomenon around the world in our given sample of the countries captures (what we call "broadening" of convergence); (ii) the rate at which countries are, on average, closing down the growth gap with the frontier; and (iii) the rate of catch-up (what we call "acceleration" for those that are catching up). The methodology to arrive at these estimates for the three levels of W-convergence follows our approach to the S-convergence, expect that in this case, we calculate the average deviations of growth rates of countries, peoples and deciles relative to those of the US in lieu of the fitted line obtained from the unconditional convergence regression.

In section V, we reevaluate the widely discussed phenomenon of middle income traps using the two notions described earlier. Section VI concludes.

Our study is closely follows and sharpens recent results which have underlined the change in global distribution of income. Barro (2016) looks at the long economic history since 1870 with the lens of conditional convergence and reinforces his earlier findings of an "iron law of convergence". However, and more importantly for us, he shows that the global income dispersion ("sigma convergence"—dispersion of levels of income across economies) has been stable between 1870 and 1950, then increased until the 1970s, and spectacularly reversed between 1980 and 2010. In a set of closely related papers, Milanovic also showed the narrowing down of global income distribution as the key driving force of recent economic history.

III. Unconditional Convergence: Solow Convergence

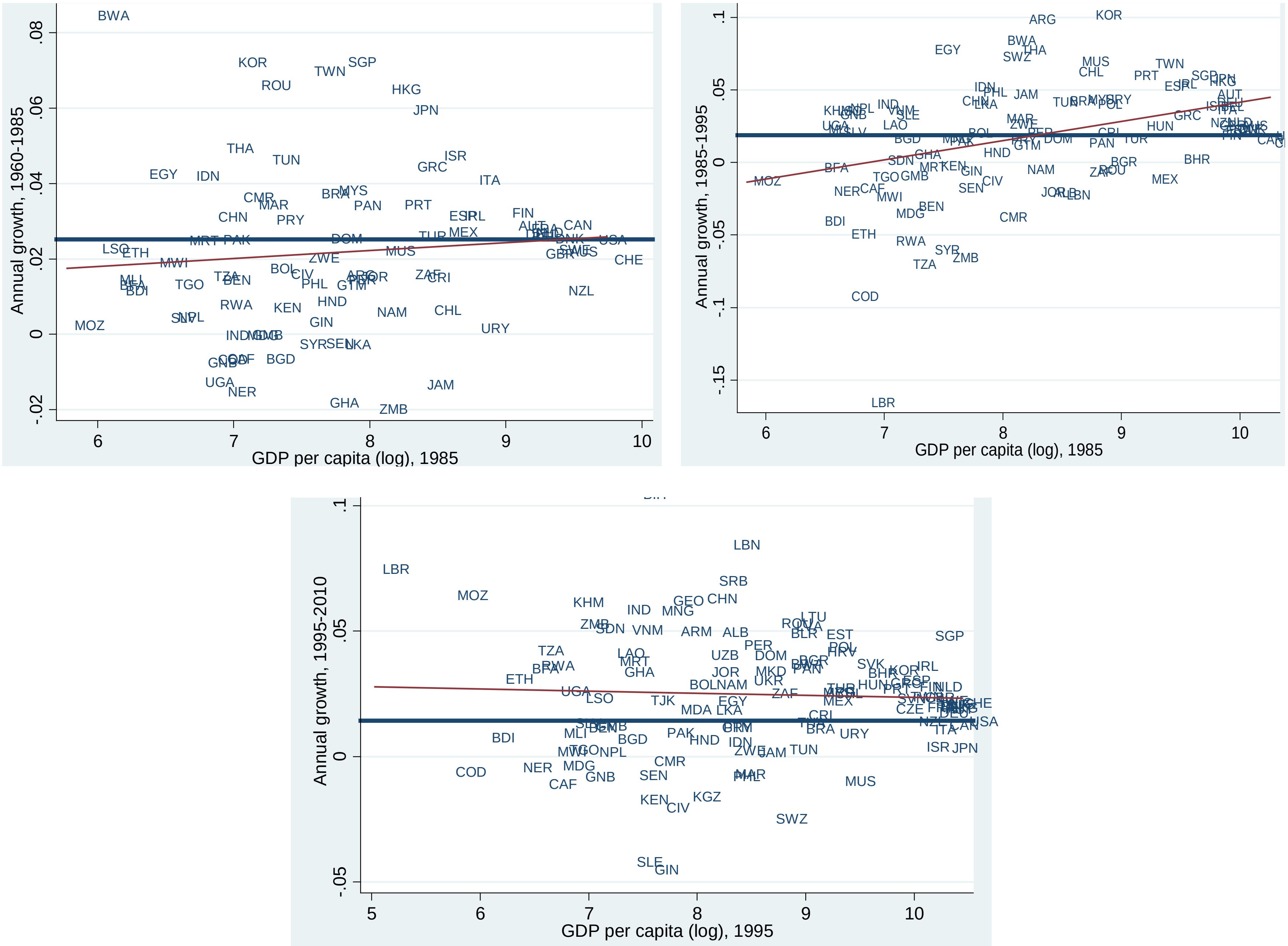
A major contribution of this paper is to document the phenomenon of unconditional convergence since the late 1980s. To contrast our findings to past studies, and also to motivate our new concept of Wilde-Convergence, we present the central stylized fact of Rodrik (2014) in Figure 1. It plots the per capita GDP growth rate of the sample of countries against their initial level of per capita GDP for three time periods.

Throughout this paper, Solow convergence will be based on the following simple regression:

$$\dot{y_t} = a + b * y_{t-1} + \varepsilon$$

where $\dot{y_t}$ is the per capita GDP growth rate over the time horizon t, and $y_{t-1}$is the level of initial per capita GDP, and b is the unconditional convergence coefficient which theory predicts should be negative. The red line is the fit of the unconditional convergence regression and the horizontal line is the per capita GDP growth rate of the United States, the reference country for Wilde-convergence. The regression line (with a slope b) is either upward sloping (earlier period) or horizontal (most recent period) both of which imply unconditional divergence. In other words, unconditional convergence has historically been altogether absent in the data. But it is worth noting two important facts which motivate our notion of Wilde-convergence: there have been a lot of countries that have grown faster than the rich countries and the United States in the earlier but especially in the later time periods; and these countries have mostly been not the poorest but those in the middle. In some ways, the absence of Solow-convergence has obscured the underlying reality of real convergence for many countries; and this obscuring has happened precisely because there may have been the opposite of the middle income trap. Because middle income countries have grown faster than the poorest countries, convergence may have been almost hidden in the data.

Figure 1: Unconditional convergence has been altogether absent in the data.



Solow 1

We run a series of unconditional convergence regressions described above.[2] But we cannot be sure that these results our representative because of the diversity of data sources and the varying time horizons and starting points. In order to establish the robustness of our results, we run the unconditional regressions for all possible combinations and summarize them in Figure 2 below. In Figure 2, we calculate the growth rates over 60, 50, 40, 30, 20, 15 and 10 years using all possible five year intervals and the three datasets. This results in a greater number of observations in the early years in our dataset (for example, sixty year growth rates can be calculated for the years 1950 and 1955, fifty year growth rates for 1960 and 1965, and so on). Moreover, given that the WDI dataset starts in 1980, the number of convergence coefficients in our pool of beta-estimates shows a sharp uptick starting that year.

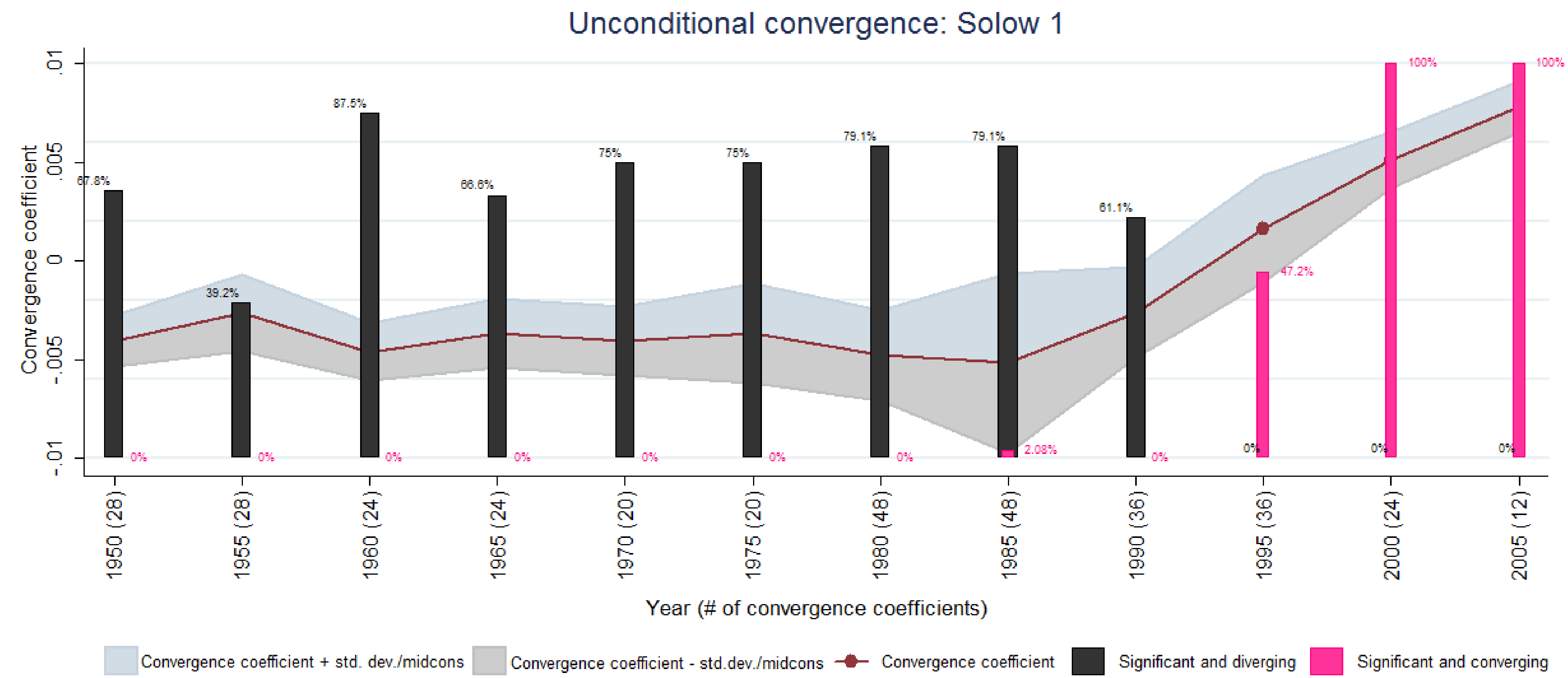
The pink bars denote the proportion of convergence coefficients that were negative (i.e. implying convergence) and significant. In order to preserve the intuition behind the main results of our analysis, we have inverted the sign of the convergence coefficient that were presented in Table 1 (that is, a negative beta coefficient implying unconditional convergence is plotted as a positive number, intended to indicate a progress towards convergence). The black bars indicate the proportion of convergence coefficients that were not negative and significant, implying divergence. The red line denotes the average value of the convergence coefficient with the shaded area capturing the [two/one] standard deviation spread around the average convergence coefficient. The integers in brackets, shown after the dates on the x-axis are the number of coefficients collected in that year. They show all the combinations of datasets and time horizons for that year.

Figure 2 illustrates our main finding: the rate of conditional convergence has sharply increased in the periods following the second half of 1990. From 1995 onwards, convergence becomes a robust phenomenon reflected in the high and rising percentage of coefficients that are significant and correctly signed. By 2005, all combinations of the data yield unconditional convergence. However, it is noteworthy that in 2000 and 2005, the magnitude of the convergence coefficient is still relative small, about 0.75 percent per year. At this rate, it would take a country about 90 years to reach half-way to its steady state output (which is also that of the frontier country). Recall that Barro suggests that the typical convergence coefficient is about 2 percent per year which implies a half-way catch-up duration of closer to 35 years.[3]

[2] Our sample throughout the paper excludes oil exporters and small countries (defined as those with a population less than 1 million in 20xx).

[3] This can be calculated by noting that the half-life, say $t*$, of a variable growing at a constant negative growth rate (say λ) is the solution to $e^{-\lambda t*} = 0.5$. Taking logs, $t* = 0.69/\lambda$.

Figure 2: Are poorer *countries* catching up on average with richer ones?



Notes: Significance at 10% confidence level. Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and smaller nations.

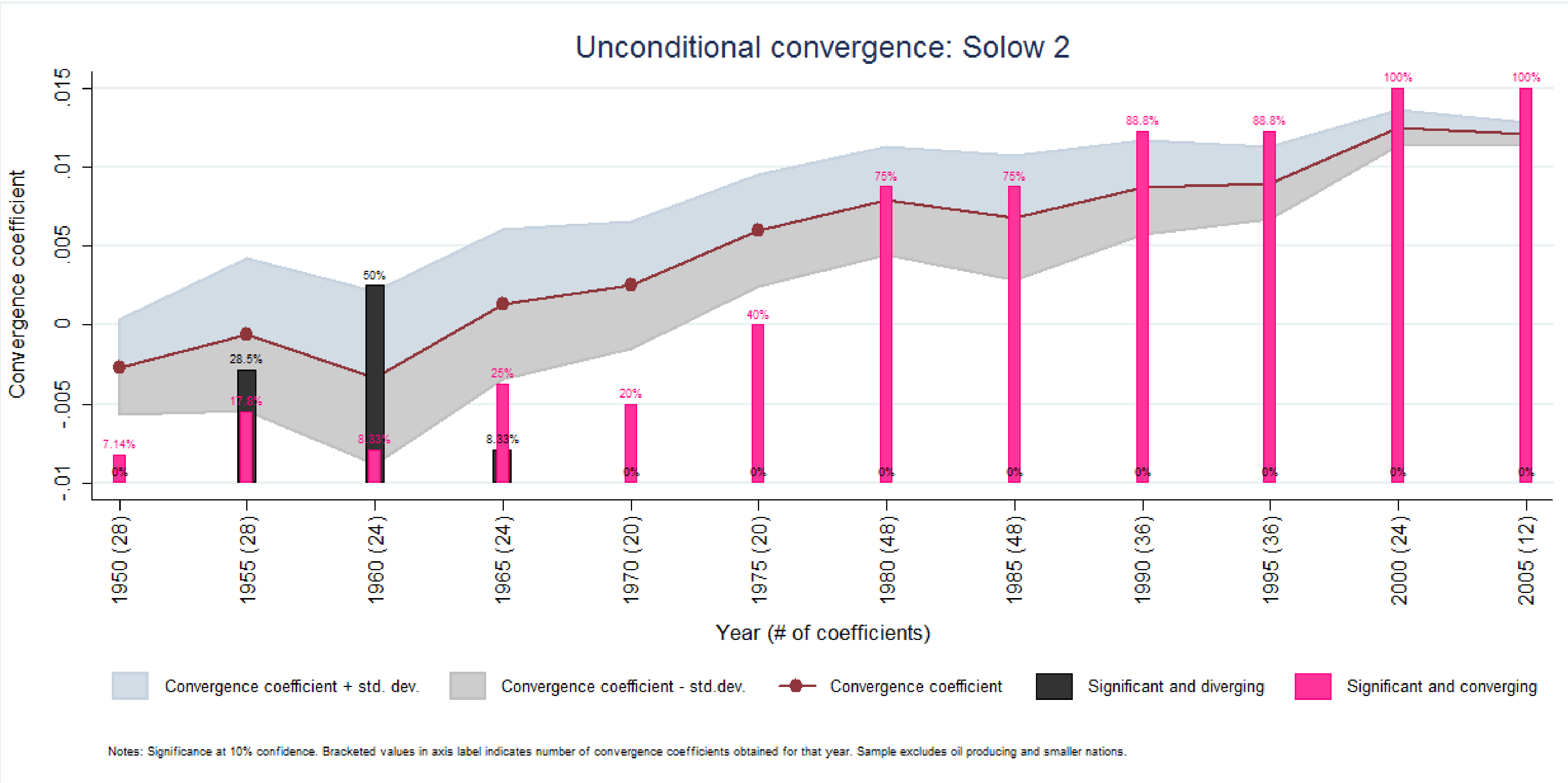
Solow 2

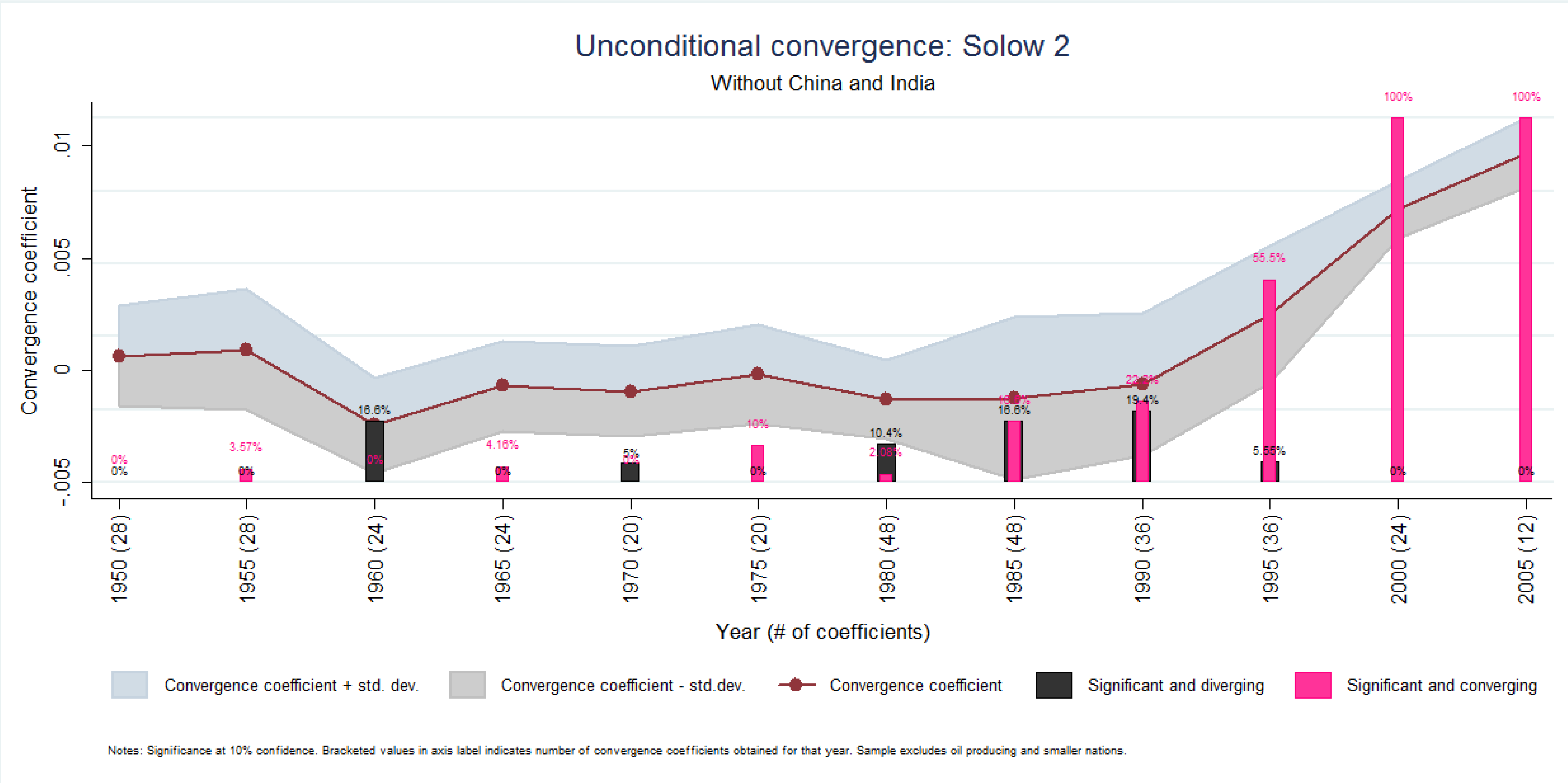
In S-2, we are interested in finding if people in poorer countries are on average catching up with people in richer countries. By weighing the initial GDP of countries with their population in the base year, we are able to estimate a population weighted convergence parameter.

We perform similar exercise Figure 3 and Figure 2, except that there is an additional combination of regressions to report for a sample that excludes China and India which are highly populous countries and which could drive the results by virtue of their size and because of the fact that they have grown rapidly.

In terms of results, Figure 3 is very different from Figure 2. Had intra-country income distribution remained unchanged, convergence at the level of people would have begun earlier than convergence at the level of countries. This is reflected in the higher percentage of significant coefficients compared with Figure 2. It is also reflected in the fact that convergence starts much earlier, the exact timing depending on whether China and India are included or not. Convergence at the level of people is also stronger in magnitude than convergence at the level of countries. The average convergence coefficient is about twice that at the level of countries. All these results are, of course, stronger when China and India are included in the analysis. The importance of this evolution is hard to overstate: since 1995, incomes have been converging, and this phenomenon has only accelerated in 2005.

Figures 3a and 3b: Are poorer people catching up on average with richer ones? (With and without China and India)





Unconditional convergence: Solow 2
Without China and India
Convergence coefficient
Year (# of coefficients)
1950 (28)
1955 (28)
1960 (24)
1965 (24)
1970 (20)
1975 (20)
1980 (48)
1985 (48)
1990 (36)
1995 (36)
2000 (24)
2005 (12)
Convergence coefficient + std. dev.
Convergence coefficient - std.dev.
Convergence coefficient
Significant and diverging
Significant and converging
Notes: Significance at 10% confidence. Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and smaller nations.

Solow 3

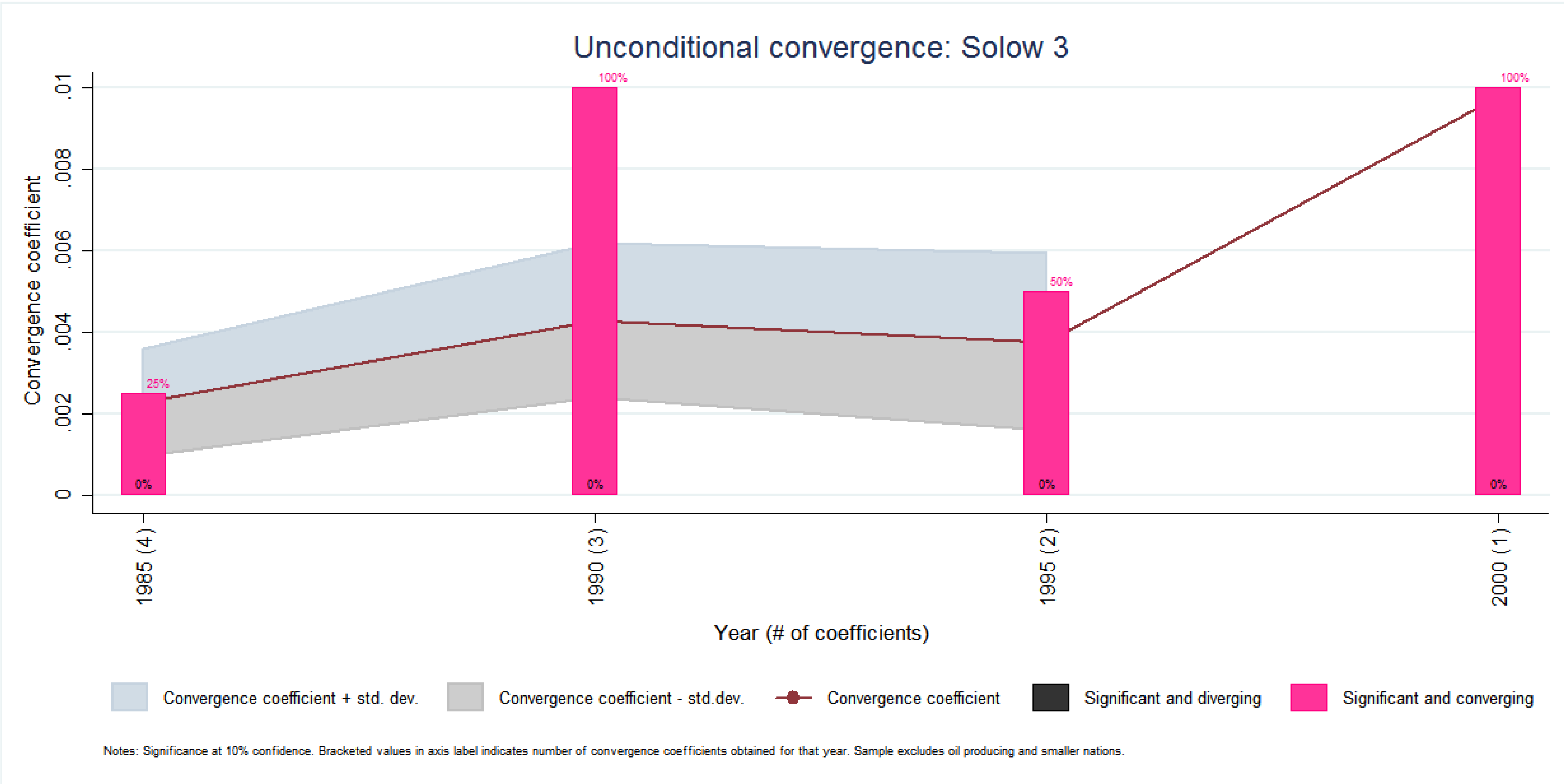
In S-3, we assess unconditional convergence across the difference segments of income distribution. We arrive at the convergence estimate by regressing the growth rate of GDP per capita at each decile at any given year to the lagged GDP per capita of the decile and weighing it by the population of the decile. This allows us to measure the rate of convergence across deciles. As focus on income within countries has increased recently, those regressions allow to test whether they tend to be a force for or against global convergence.

Relying on PovcalNet/LIS for the underlying income distribution data, we run our estimates on a panel spread over 1977 to 2011. Using the strategy outlined in Data Appendix, we are able to convert the unbalanced PovcalNet data to a balanced panel of five year intervals. This then allows to calculate growth rates over 30, 20, 15 and 10 years. Thus in S-3 we are able to present the results of convergence from only one dataset (as opposed to three in S-1 and S-2), implying that we obtain 4 beta estimates for 1975 and 1980, 3 estimates for 1985 and 1990, 2 estimates for 1995 and 1 estimate for 2000. The pooled beta estimates are presented in Figure 4.

The Figure shows that unconditional convergence at the level of people has been happening with a vengeance since 1990, reflected in the fact that most coefficients are significant (in both samples with and without China). The Figure shows a sharp rupture with the period before (1985) when all the coefficients were insignificant. What is surprising that the magnitudes are not large: in the most recent period the convergence co-efficient is about 1 percent in both samples, suggesting that catch-up at the level of people will happen relatively slowly. These magnitudes are close to those obtained under S1 convergence. Surprisingly, the exclusion of China and India neither affects the spread of convergence nor its pace. The line of fit for years 2000 and 2010 shown in Figure 4(c) shows that this observation is driven by lower income deciles of India rather than China. Given that these deciles fall below the line of fit, i.e., the Indian lower deciles have not proportionately increased as rapidly as their Chinese counterparts, the exclusion of both countries has a balancing effect on the pace and spread of convergence in both samples.

The other possible reason could be that there are two influences at work in these two countries: average growth rates are high, reinforcing convergence; but inequality which leads to slower growth at lower deciles, holds back convergence

Figures 4a and 4b: Are poorer people catching up on average with richer ones? (With and without China and India)



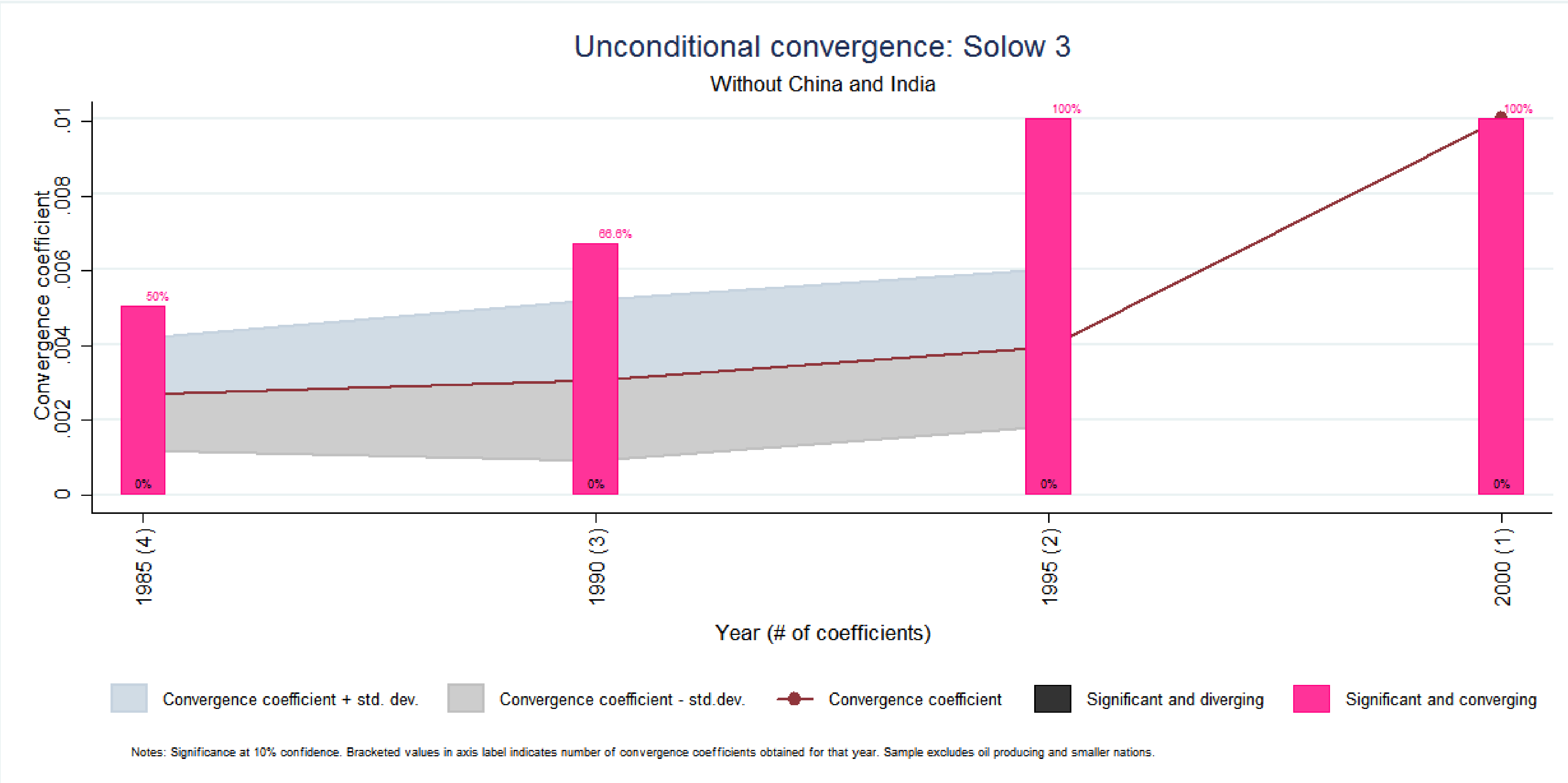
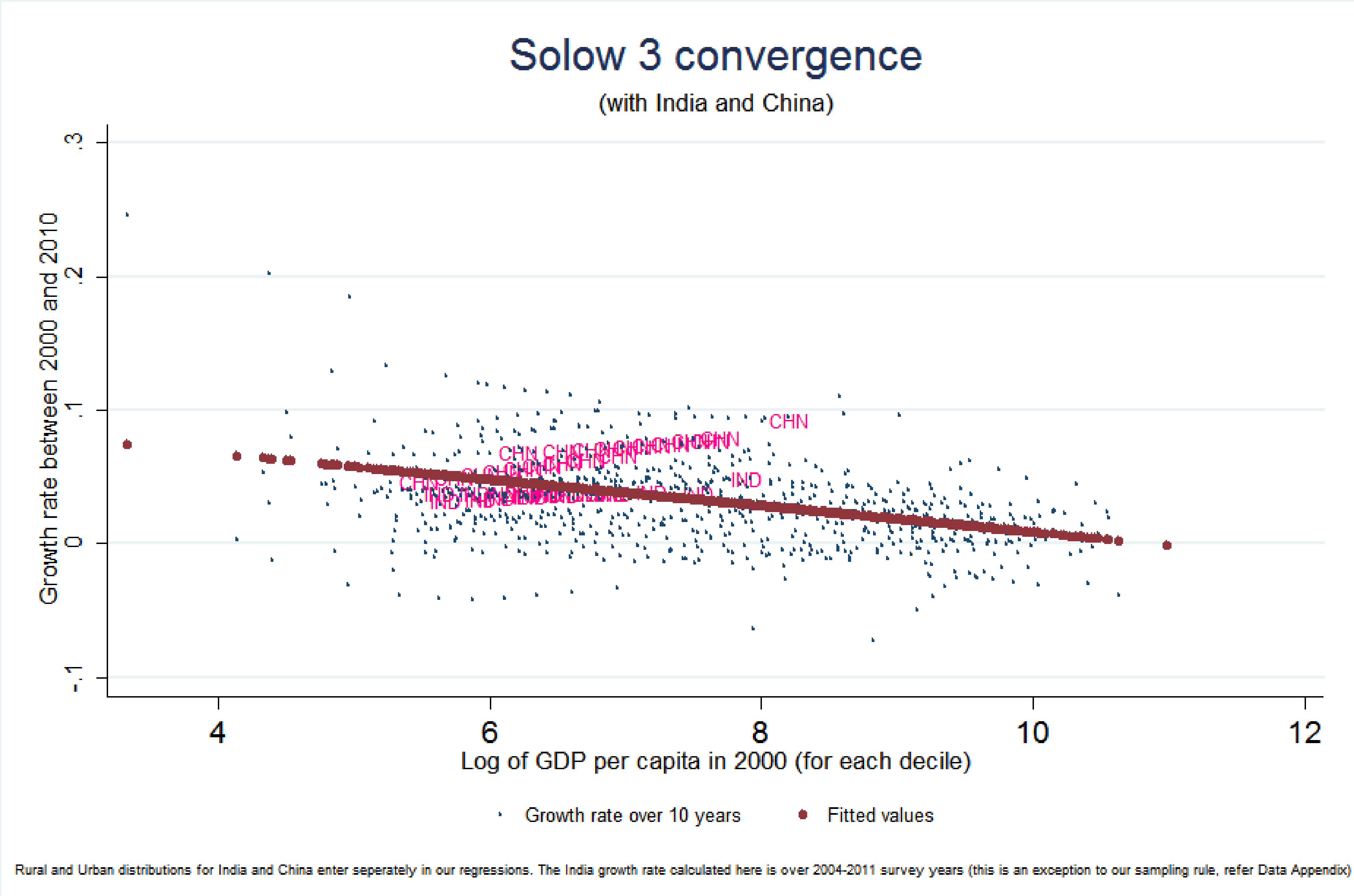

Unconditional convergence: Solow 3
Without China and India
Convergence coefficient
0
.002
.004
.006
.008
.01
50%
66.6%
100%
100%
0%
0%
0%
0%
1985 (4)
1990 (3)
1995 (2)
2000 (1)
Year (# of coefficients)
Convergence coefficient + std. dev.
Convergence coefficient - std.dev.
Convergence coefficient
Significant and diverging
Significant and converging
Notes: Significance at 10% confidence. Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and smaller nations.

Figure 4c: Indian deciles grew slower than their Chinese counterparts.



IV. Unconditional Convergence: Wilde Convergence

Wilde convergence denotes a different concept of catching-up, but it is probably as, if not more, intuitive. S-convergence is an average concept (are countries, people or poorer-people growing faster on average than other richer countries, people in richer countries or richer people?). Under S-convergence we cannot single out or count the countries that are converging. Moreover, average behavior—between rich and poor—can be confounded by behavior within rich and poor as well. W-convergence is simpler and because it is a comparison relative to a fixed point, different aspects of convergence can be identified—how many countries and people are catching up with their counterparts in the reference country (in our baseline case United States). Thus, our analysis of W-convergence not only serves to complement our results in S-convergence, but also serves as robustness check to the above analysis. It also allows us to emphasize the breadth of convergence (how many countries/people?) and the speed (how much faster do they grow compared to the frontier?).

Wilde 1

W-1 is similar to S-1 in that we are interested in the average rate at which *countries* are growing relative to the United States. As noted earlier, and unlike with reference to Solow convergence, we can provide three statistics to summarize W-convergence: coverage, namely the number and proportion of countries that are growing faster than the US in the sample; and the speed of convergence measured either as the average difference between growth rate of all countries and the US, or the average difference between growth rates of US and the countries that are growing faster than the US). The table below illustrates the various indicators we use to capture Wilde convergence for a particular combination of datasets and time horizons.

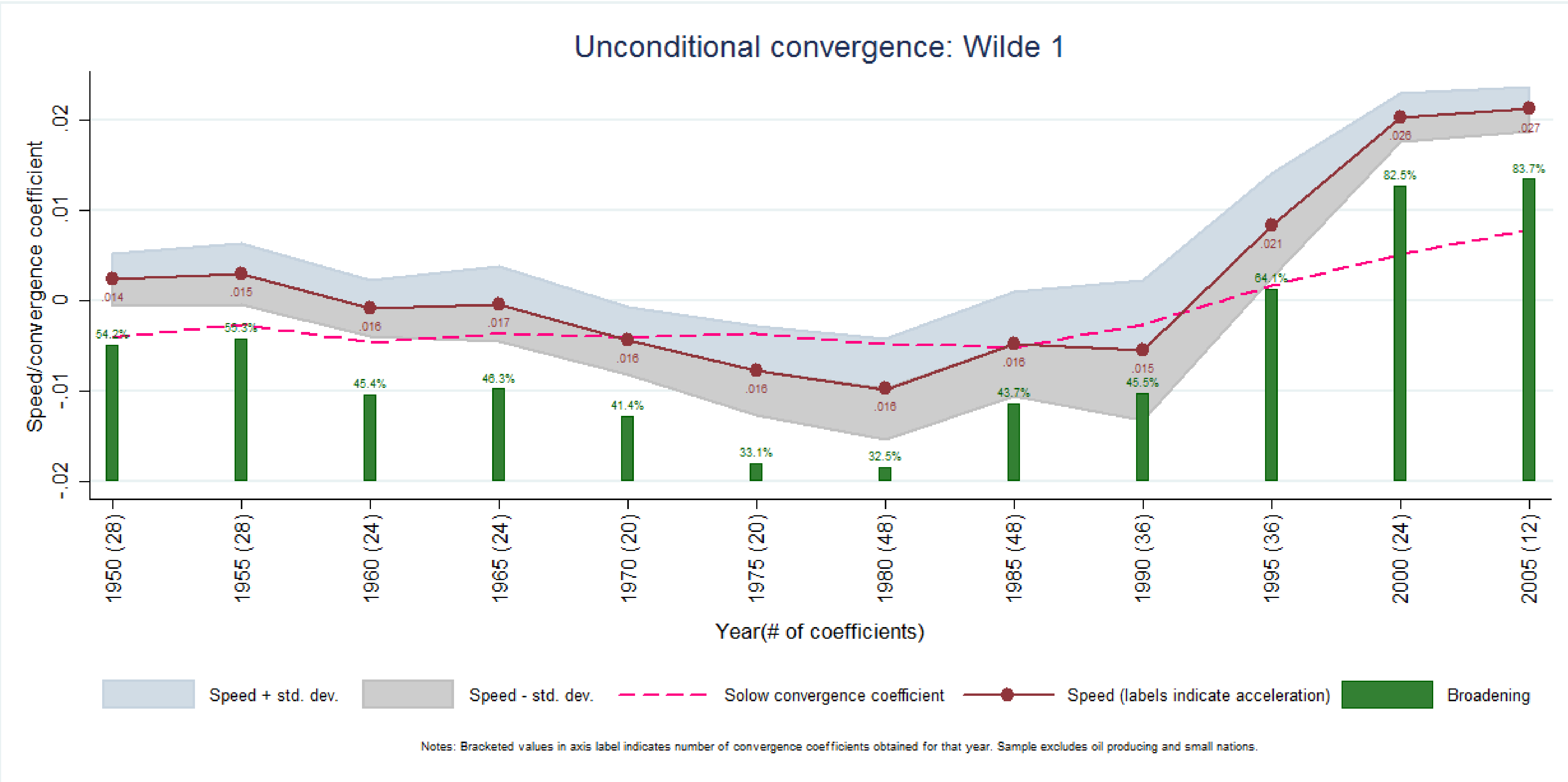
We generalize these results and establish their robustness, for the different samples, time horizons and starting points, in the Figures below.

Table 4: Countries converging to the United States for a sample of years

	PANEL A: Divergence			PANEL B: Strong Convergence		
	Maddison	PWT	WDI	Maddison	PWT	WDI
DV: Growth rate	1960 and 1980	1965 and 1995	1980 and 1990	1990 and 2010	1985 and 2015	2000 and 2010
Speed of convergence	**-0.0033**	**-0.00898**	**-0.0205**	**0.00612**	**0.0033**	**0.0236**
Acceleration	**0.0151**	**0.02076**	**0.0208**	**0.01749**	**0.01568**	**0.0297**
Broadening	**35.5%**	**30.3%**	**20.8%**	**66.2%**	**56.6%**	**85.4%**
Countries in sample	**93**	**66**	**72**	**74**	**76**	**96**

Notes: Sample throughout: non-oil and non-small (< 1 mn. in 2010) and includes China and India. Countries in sample $= \mathrm{n}$; number of countries converging cv; broadening $= \frac{\mathrm{cv}}{\mathrm{n}}$; speed $= \frac{\sum \dot{y}_1}{\mathrm{n}} - y_{\dot{US}}$; acceleration $= \left(\frac{\sum \dot{y}_1}{\mathrm{cv}} - y_{\dot{US}} \mid i\ \varepsilon\ (\dot{y}_1 > y_{\dot{US}})\right)$

Figure 5: Are poorer countries catching up on average with United States?



The green bar indicates the number of countries that are catching up (broadening), with the associated numbers given just above the bars. We denote the average point estimate of W-convergence in maroon and the spread of two standard deviations with the blue bars; the maroon thus captures the average speed of convergence (across the entire sample of convergers and non-convergers). The number in maroon, in contrast, indicates the speed of convergence for those that are converging only (which we call acceleration). The integers at the bottom, as earlier in S-convergence, denote the number of combinations over which the basic convergence statistics are computed. In order to compare W-convergence with S-convergence we also plot the average estimates of S-1 convergence in the secondary axis (reproducing the basic information in Figure 2).

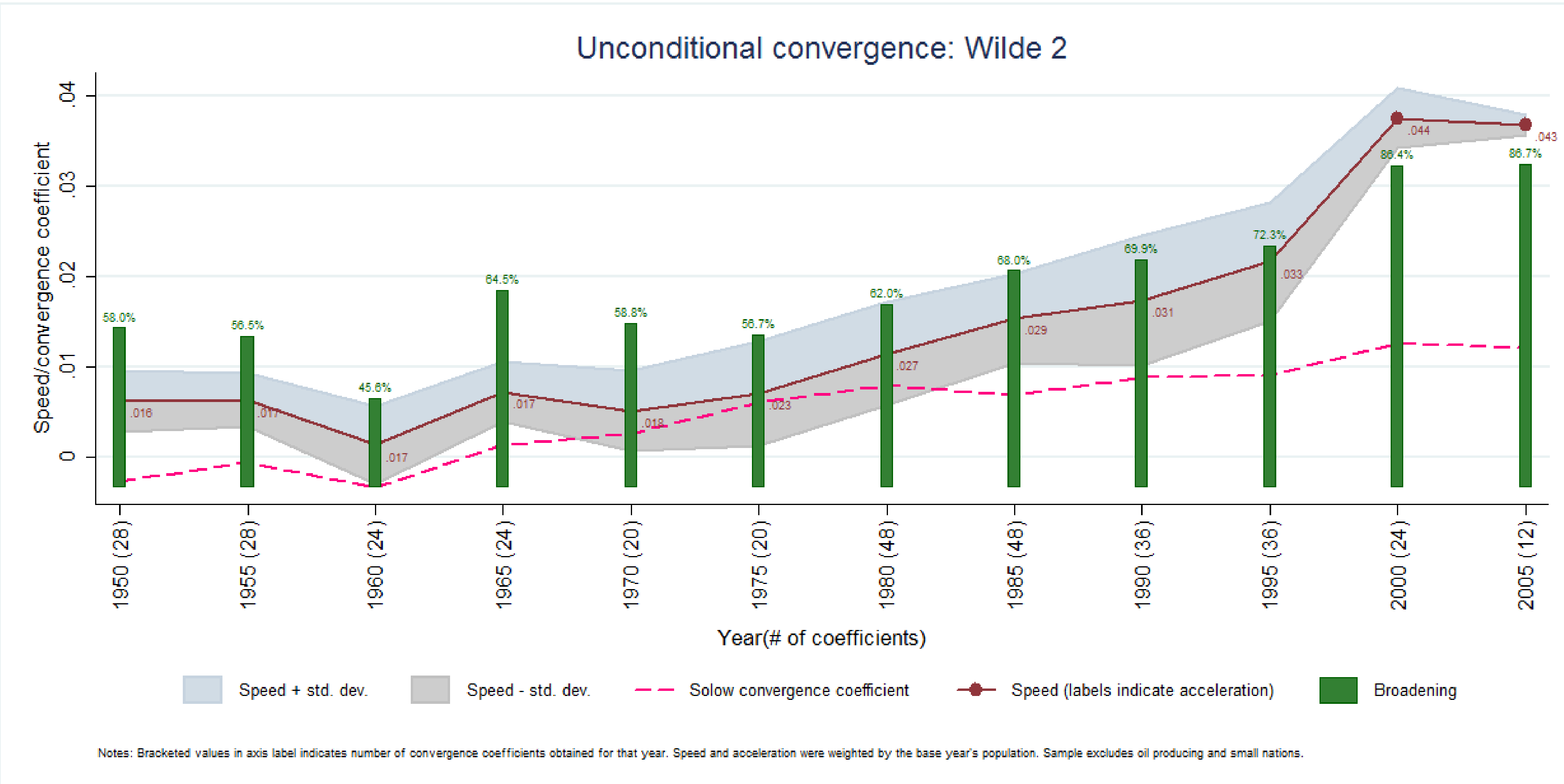
A number of observations emerge from this figure, the most striking being the contrast with the results from Solow convergence. First, there is robust evidence of Wilde convergence. Beginning in 1985, a growing number of countries have been converging to the frontier (almost 45 percent in 1985 and rising to about 85 percent in the most recent periods). Second, they have been converging at an accelerating pace, from about 1.6-1.7 percent in the 1980s to 2.7 percent in the most recent periods. This is what one might call "convergence with a vengeance": more countries are catching up with the frontier in terms of average standards of living (broadening of convergence) and are doing so at a faster pace (acceleration of convergence). An average convergence rate of 2.7 percent implies that a half-way catch-up with the US will happen in about a quarter of a century, which is much less gloomy than the estimates suggested by the Solow convergence framework.

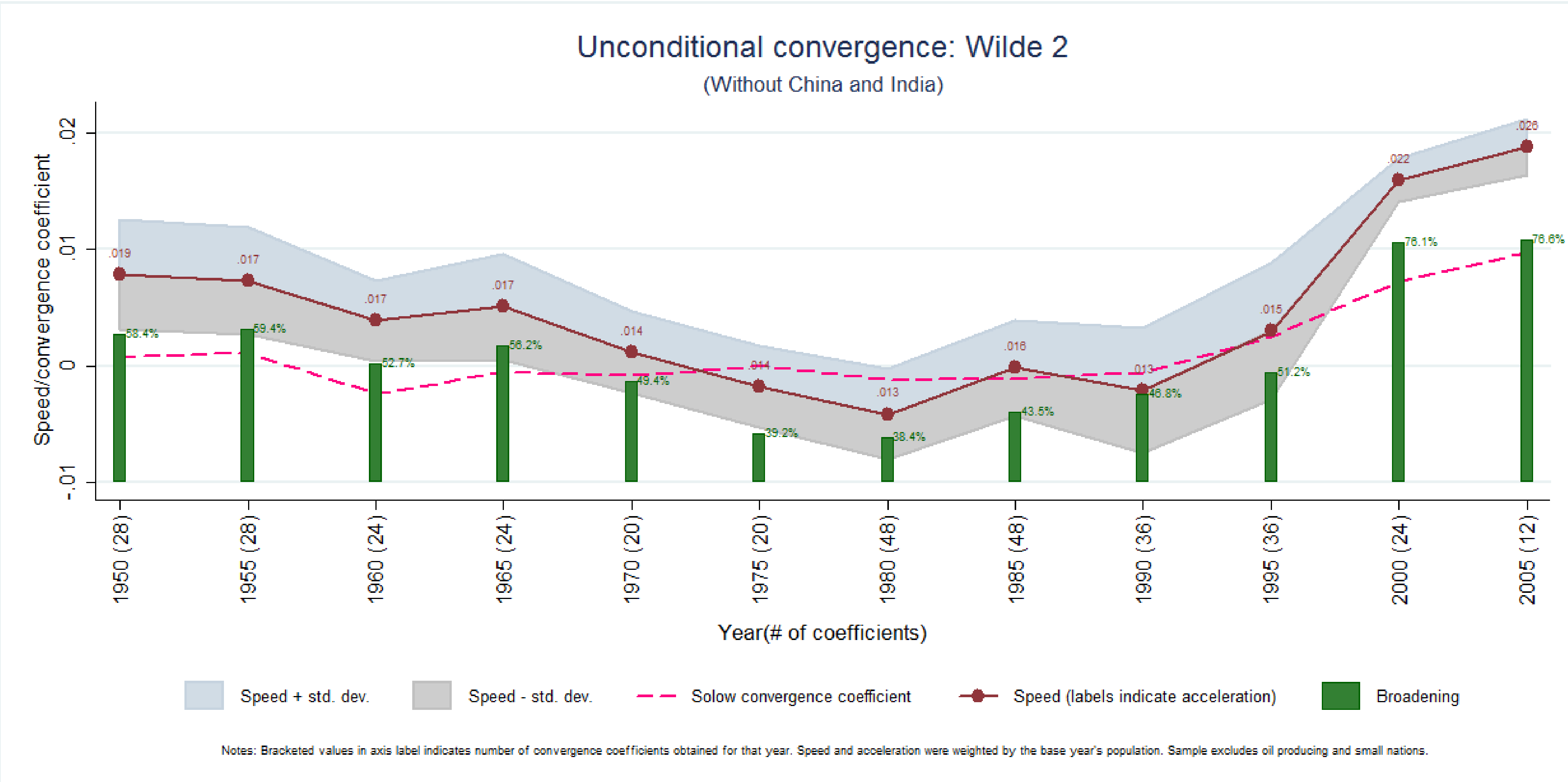
The average S-convergence coefficient (shown in the red dotted line) is well below the maroon dot and well below the red numbers and on a different and lower scale than that of W-convergence. For example, in 2000, the average W-convergence coefficient is close to 2.7 percent while the S-convergence coefficient is close to 0.5 percent or about 25 percent of W-convergence.

Wilde 2

W-2 follows from S-2 in assessing if *people* in poorer countries are on average catching up with the average person in the United States. The average speed and acceleration of convergence in W-2 is now estimated by weighing the growth rates of GDP per capita by the population in the base year. Since W-2 assesses the extent of convergence for the average person, broadening now implies the proportion of world's population that experiences, on average, a growth rate higher than the average person in the US. We pool our estimates for all years in Figure 6.

Figure 6: Are people on average catching up on with the average person in the United States?




Unconditional convergence: Wilde 2
(Without China and India)
Speed/convergence coefficient
-.01
0
.01
.02
.019
.017
.017
.017
.014
.014
.013
.016
.013
.015
.022
.026
58.4%
59.4%
52.7%
56.2%
49.4%
39.2%
38.4%
43.5%
46.8%
51.2%
76.1%
76.6%
1950 (28)
1955 (28)
1960 (24)
1965 (24)
1970 (20)
1975 (20)
1980 (48)
1985 (48)
1990 (36)
1995 (36)
2000 (24)
2005 (12)
Year(# of coefficients)
Speed + std. dev.
Speed - std. dev.
Solow convergence coefficient
Speed (labels indicate acceleration)
Broadening
Notes: Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Speed and acceleration were weighted by the base year's population. Sample excludes oil producing and small nations.

The following conclusions can be drawn from the chart. Had income distributions not changed within developing countries, the scope and speed of convergence of people residing there relative to the United States would have been spectacular. This is what W-2 convergence implies. The key difference with W-1is the speed of convergence: in a sample that includes China and India, the speed of convergence has risen from 2 percent in 1970 to about 4.2 percent in the most recent periods. Even without China and India, the speed is now close to 3 percent. And comparing W-convergence with S-convergence (shown on the secondary axis) suggests that the former is happening at a much more rapid pace.

Wilde 3

W-2 convergence was a notional one because it assumed (contrary to the reality) that income distribution within countries remained unchanged. W-3 is based on actual income distributions in countries. In W-3 we compare people in different parts of their country's income distribution to the median person in the US. We calculate the three statistics in the same way as W-2 except that our cross-section is a tuple of country and decile rank. Thus the speed of convergence is the population-weighted average of the differences between growth rates of all (decile, country) tuples and the median income in the US weighted by the population in the (decile, country) tuple; broadening is the proportion of people in the (decile, country) tuple that have grown faster than the median US income, and; acceleration is the same as speed but the averages are calculated for only those (decile, country) tuples that have a higher growth rate than the median US income.

As in S-2, relying on PovcalNet/LIS produces an unbalanced panel which is addressed by the methodology outlined in Data Appendix to convert it into a balanced panel. We calculate the four possible growth rates over 25, 20, 15 and 10 years. The complete set of results for all years are presented in Figure 7.

The Figures illustrate a number of points. Especially since 1985, and in terms of living standards, nearly 90 percent of the world's population has been catching up with standards in the US. Clearly, this is more true of the sample that includes China and India. But it is also substantially true of the sample without. For example, in the former sample, in 1990 nearly 90 percent of the world's population was catching up, and in the latter sample it was 70 percent. So, at the level of people Wilde-convergence had started earlier (around the 1980s) than suggested by the Solow framework (mid-1990s).

The second noteworthy feature is the pace of catch-up: in the sample with China and India, this amounted to about 2.2 percent in 1990 and a torrid 4.3 percent in 2000, the latter implying a half-life catch-up with the frontier of sixten years. Third, the average Solow convergence coefficient is also plotted in these figures which is consistently below the Wilde convergence coefficient. Figures 7 and the other results in the Wilde framework suggest the broader inference that the Solow convergence framework was seriously misleading about the timing (1980s in Wilde versus 1990s in Solow), breadth (broad, nearly covering all countries and all people in Wilde versus narrow in Solow), and pace (rapid in Wilde at a rate of between 3 and 4.5 percent and tepid in Solow at the rate of less than 1 percent) of convergence both at the level of countries and of people. Solow held us in thrall to the narrative of pessimism about the performance of the developing world.

One final question pertaining to Wilde convergence is whether our results reported in the Wilde measures are sensitive to the choice of US as the comparator country (representing the global economic frontier) Appendix xx plots the Figures to highlight the differences between using US and other options; but, the overall conclusion we arrive is that: it is more appropriate to choose one country that is representative of the frontier throughout the entire period of our analysis. For example, had we included Japan (given its current high income status) as the Wilde comparator country, the results would have been misleading as Japan was not an advanced economy for much of the time covered in our analysis. Second, even if we replaced the US with a set of advanced European economies, the results do not change much, at least for the period (post-1990) when convergence with a vengeance has repeatedly manifested itself.

Figures 7a and 7b: Are poorer people catching up with the median person in the US?


Unconditional convergence: Wilde 3
Without China and India
Speed/convergence coefficient
0
.005
.01
.015
.02
.025
86.2%
72.8%
76.9%
84.8%
.016
.015
.014
.033
1985 (4)
1990 (3)
1995 (2)
2000 (1)
Year(# of coefficients)
Speed + std.dev.
Speed - std.dev.
Solow convergence coefficient
Wilde Speed (labels indicate acceleration)
Broadening
Notes: Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and small nations.

V. The Middle Income Trampoline: Solow Convergence

The first section of this paper established that while economic divergence was a dominating global phenomenon preceding the 80s, since then there is strong evidence in support of economic convergence globally. However, a recent literature has argued that convergence was easier at low levels of income. The "China, 2030" report (World Bank, 2013) underlined that only 13 countries have graduated from middle to high-income status, and warned against a potential "middle income trap". This idea has since received empirical and theoretical support: Eichengreen, Park and Shin (2013) find a growth slowdown around $15,000 of 2005 PPP dollars, Aiyar, Duval et al. (2012) use a more rigorous convergence framework and also find evidence of lower growth at some levels of income. However, the concept has attracted some suspicion: Pritchett and Summers (2014) attribute the middle income trap to an illusion linked to mean-reversion phenomena.

In this paper, we use the simple unconditional convergence framework to analyze the middle income trap (MIT). Since there is a lot of confusion about what MIT means, we specify two notions of MIT[4].

	Notion 1	**Notion 2**
QUESTION	Are middle income countries (on average) negative outliers in an unconditional convergence framework that includes all countries?	Are middle income countries (on average) negative outliers in an unconditional convergence framework that includes only MICs and advanced countries?
TEST	Is the MIC dummy negative and significant in an unconditional convergence regression? If not, there is no MIT	Is the MIC dummy negative and significant in an unconditional convergence regression for a sample that includes only MICs and Advanced countries? If not, there is no MIT

In the first notion, the idea is to ask whether MICs grow "normally" in a sample comprising all countries; that is, whether it is easier to grow and converge at lower rather than middle levels of income. The second notion is different: having reached middle income status, do MICs grow in such a way as to put them on the path—or converge normally--to becoming advanced countries. So, this question relates to whether MICs grow normally in a sample that comprises only MICs and advanced countries.

[4] Note that we do not estimate any Wilde convergence measures in this section. One reason is to avoid a combinatorial explosion of possibilities (six more for the two notions associated with the three Wilde concepts) that would clutter the paper and distract from the important findings. Second, by definition the Middle Income Trap would require us to compare a certain *group* of countries with another *group*. A fixed comparator, which is intrinsic to our notion of Wilde convergence would thus sit uneasily with assessing the MIT.

The way to test these notions of MIT is to run the following regression:

$$\dot{y_t} = a + b * y_{t-1} + a_{mid} * Mid_{t-1} + \varepsilon$$

Here Mid is the middle income dummy. For notion 1 the sample includes all countries; for notion 2 the sample is restricted only to middle income and advanced countries.

If and only if a_{mid} , the coefficient of the middle income dummy is negative and significant is there a MIT. That is what we proceed to test below.

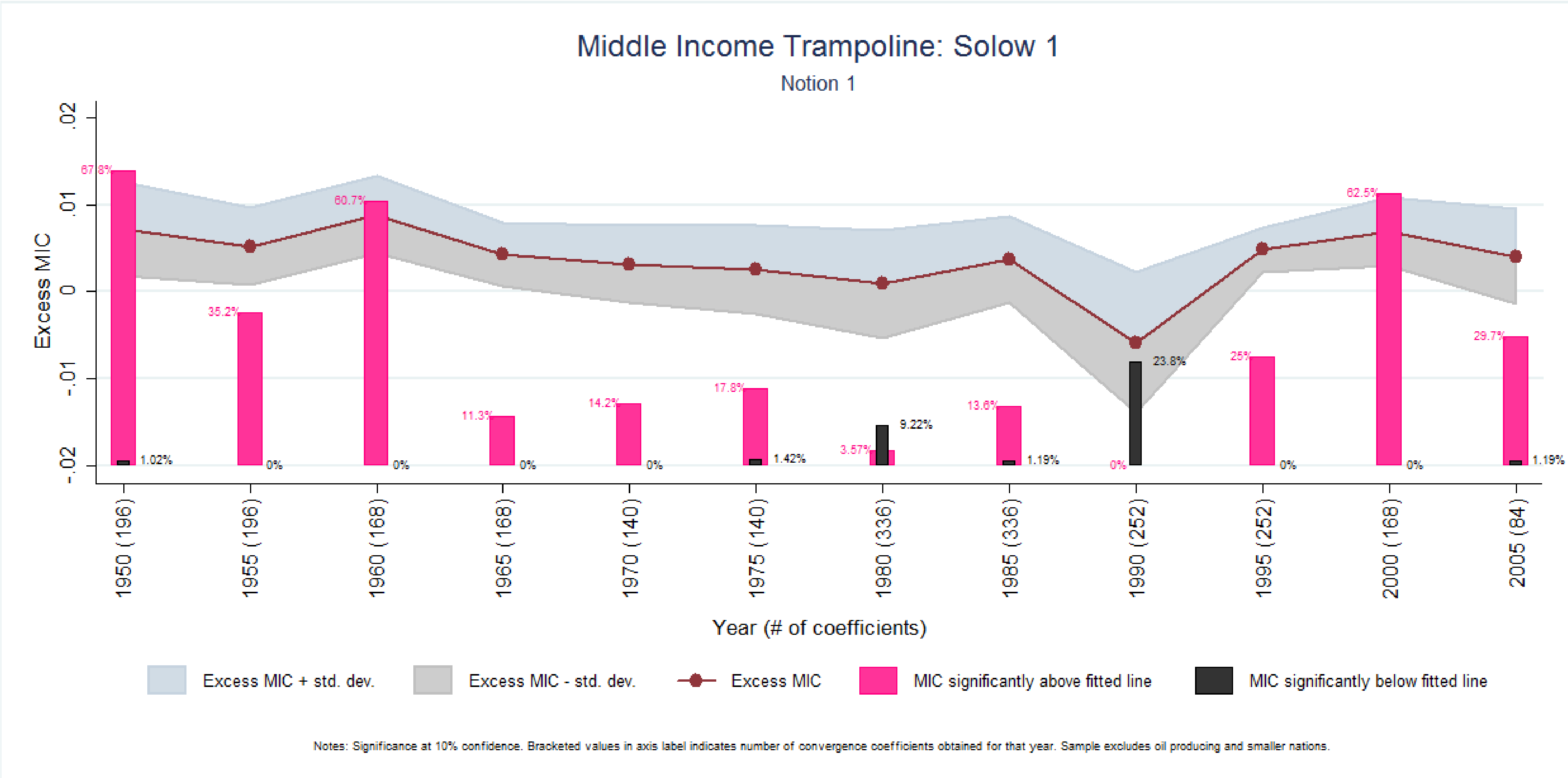
One difficult question relates to definition: what is a middle income country? While some intuitive concepts exist (belonging to the OECD, being classified as LIC by the World Bank, etc.), the truth is that there is no good or even widely accepted answer. Indeed, as discussed in Subramanian (2011), this lack of a good answer is reflected in the frequent and tortuous taxonomic tweakings over time by the IMF in categorizing countries.

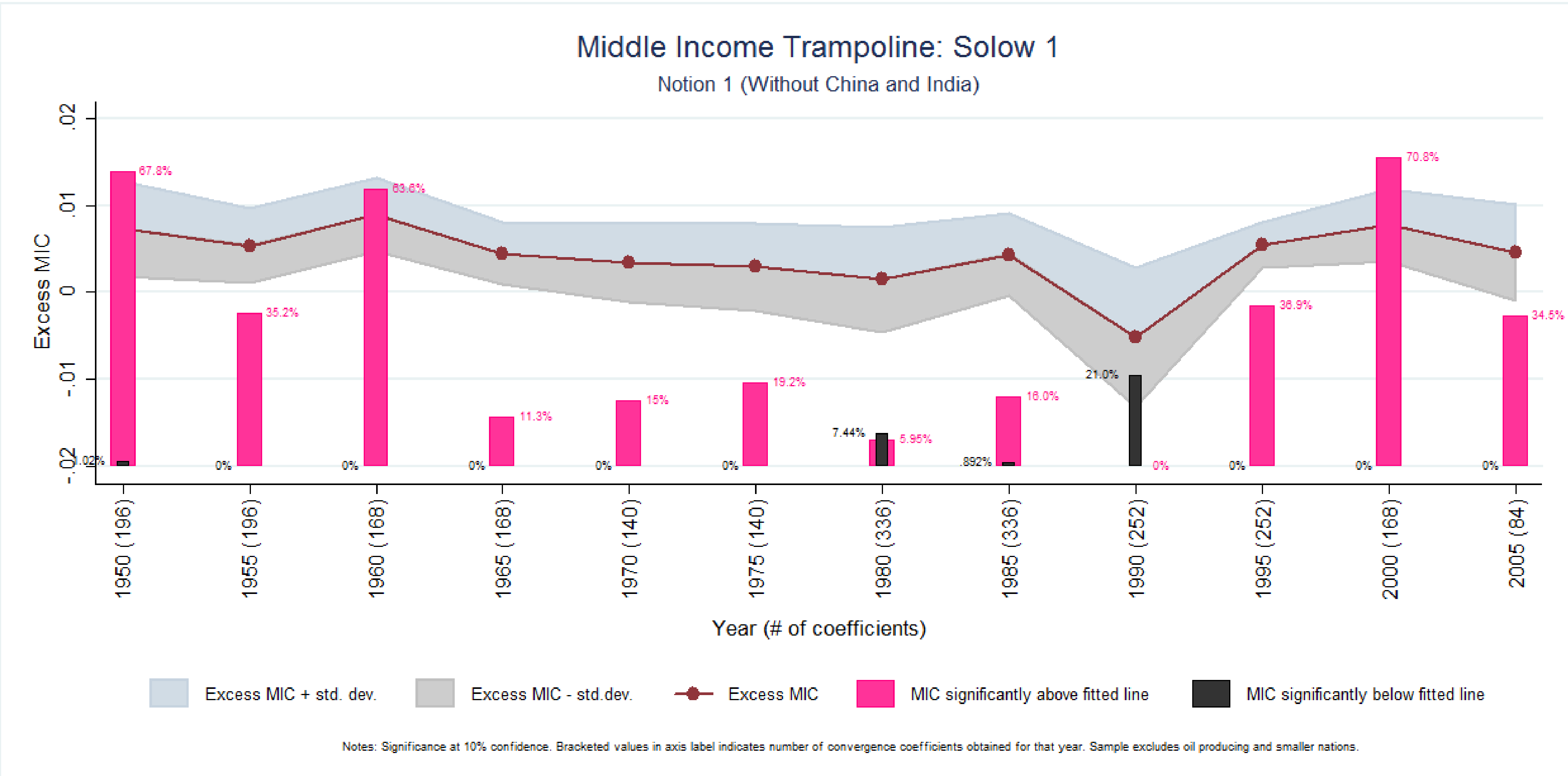
Instead of trying to fix a definition, we adopt a more flexible approach, allowing for a range of plausible definitions of MICs. Following Aiyar (2013), we assign a country the Middle Income Status if its GDP per capita ranges between 15-40 percent, 15-45 percent, 15-50 percent, 20-40 percent, 20-45 percent and 20-50 percent of US GDP per capita. Every such definition yields a corresponding definition of low income and high income: that is, if an MIC falls in the 15-40 percent range, the LIC falls in the less than 15 percent range and the HIC in the greater than 40 percent range. In addition, we also use the World Bank's Low and High Income classification as a robustness check. Thus, with three datasets as earlier, 7 possible growth rates spread over 65 years of data, we also obtain 7 (6+1) additional estimates for each possible classification of middle-income countries. We average out for each period the coefficients for each concept. While imperfect (each reader might have her preferred classification), this approach allows us to remain agnostic and consistent on the exact definition of a middle income country.

Middle Income Trap (MIT): Solow 1 Notion 1

Figures 8 and 9 below plot the results for testing the Middle Income Trap at the level of countries (Solow 1) and in terms of notion 1. In each chart, the percentage of times the MIC dummy is negative and significant is shown in black (a necessary and sufficient condition for the existence of a MIT) and the number of times it is positive and significant is shown in pink. In addition, the average value of the MIC dummy and a 1 percent confidence band around it are also plotted. For each time period, the number of replications of the unconditional convergence regression are shown on the x-axis in parentheses. Recall that there are multiple combinations of data sets, definitions of middle income, and time horizons at each point in time that the regression is run. The chart speaks clearly: there is no MIT because instances of black bars are rare; the MIC dummy is mostly positive and significant, suggesting that they grow faster than the average country conditional on the initial level of income. Only for the period 1990, is the MIC dummy negative and significant and that too only in 20 percent of the replications.

Figures 8(a) and 8(b): Is there a Middle Income Trap at the level of all countries?




Middle Income Trampoline: Solow 1
Notion 1 (Without China and India)
Excess MIC
.02
.01
0
-.01
-.02
67.8%
35.2%
63.6%
11.3%
15%
19.2%
7.44%
5.95%
.892%
16.0%
21.0%
36.9%
70.8%
34.5%
1.02%
0%
1950 (196)
1955 (196)
1960 (168)
1965 (168)
1970 (140)
1975 (140)
1980 (336)
1985 (336)
1990 (252)
1995 (252)
2000 (168)
2005 (84)
Year (# of coefficients)
Excess MIC + std. dev.
Excess MIC - std.dev.
Excess MIC
MIC significantly above fitted line
MIC significantly below fitted line
Notes: Significance at 10% confidence. Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and smaller nations.

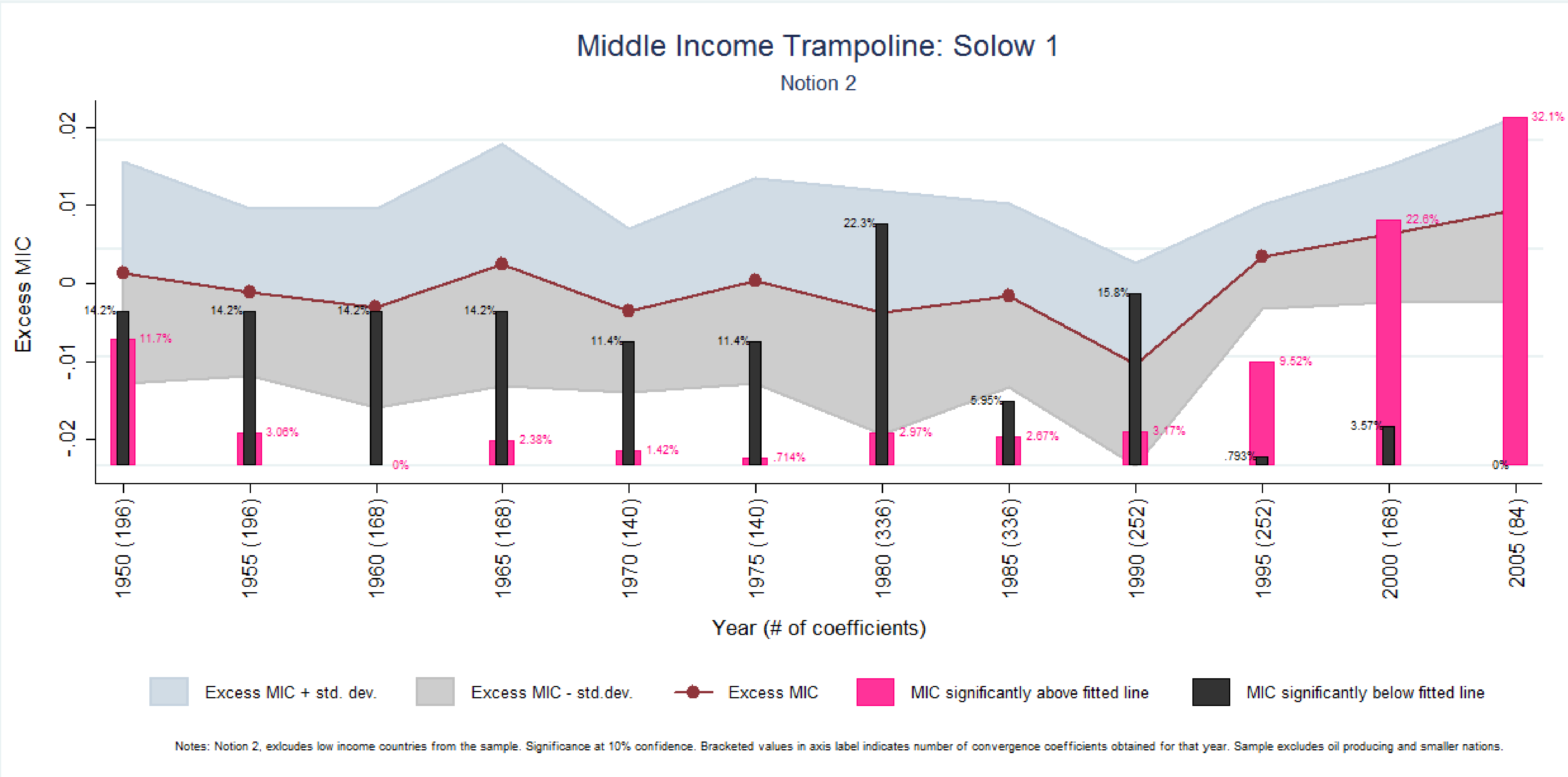
Solow 1 Notion 2

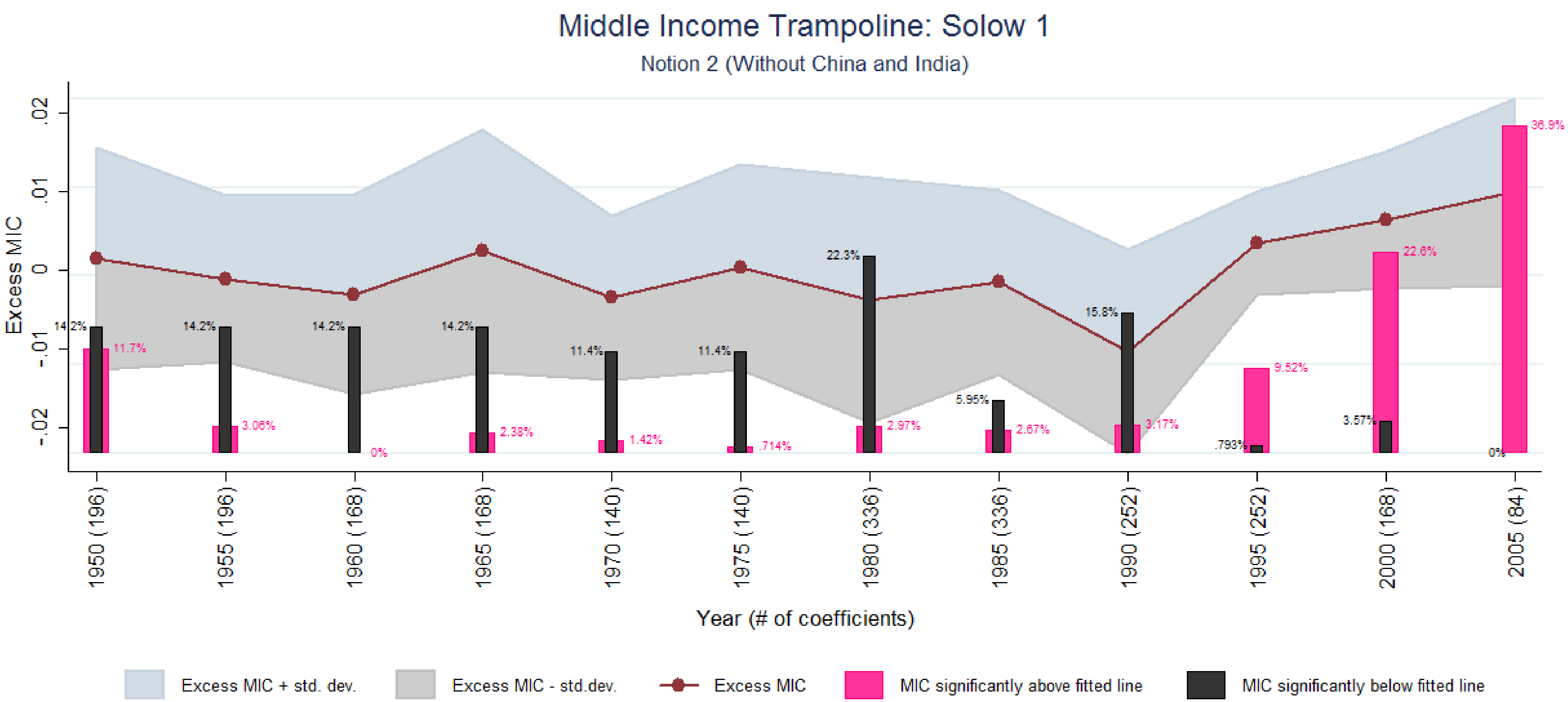
If MICs are normal in general, is there something to the allegation that it is easy to *become* a MIC but difficult to move beyond. Figure 9 plots the results.

While there are many more times when the middle income countries seem to grow slower than ACs (correcting for per capita GDP)—and hence more black bars—(compare Figure 9 with 8) that proportion is not high, and about 22 percent at its peak in 1980.

Moreover, even in Figure 9 it is worth noting that in the most recent periods (since 1995), there are many more instances when they seem to be growing even faster than convergence would predict (positive and significant coefficient) and very few instances where they are growing significantly slower (black bars).

Figures 9(a) and 9(b): Is there a Middle Income Trap at the level of middle income and advanced countries?





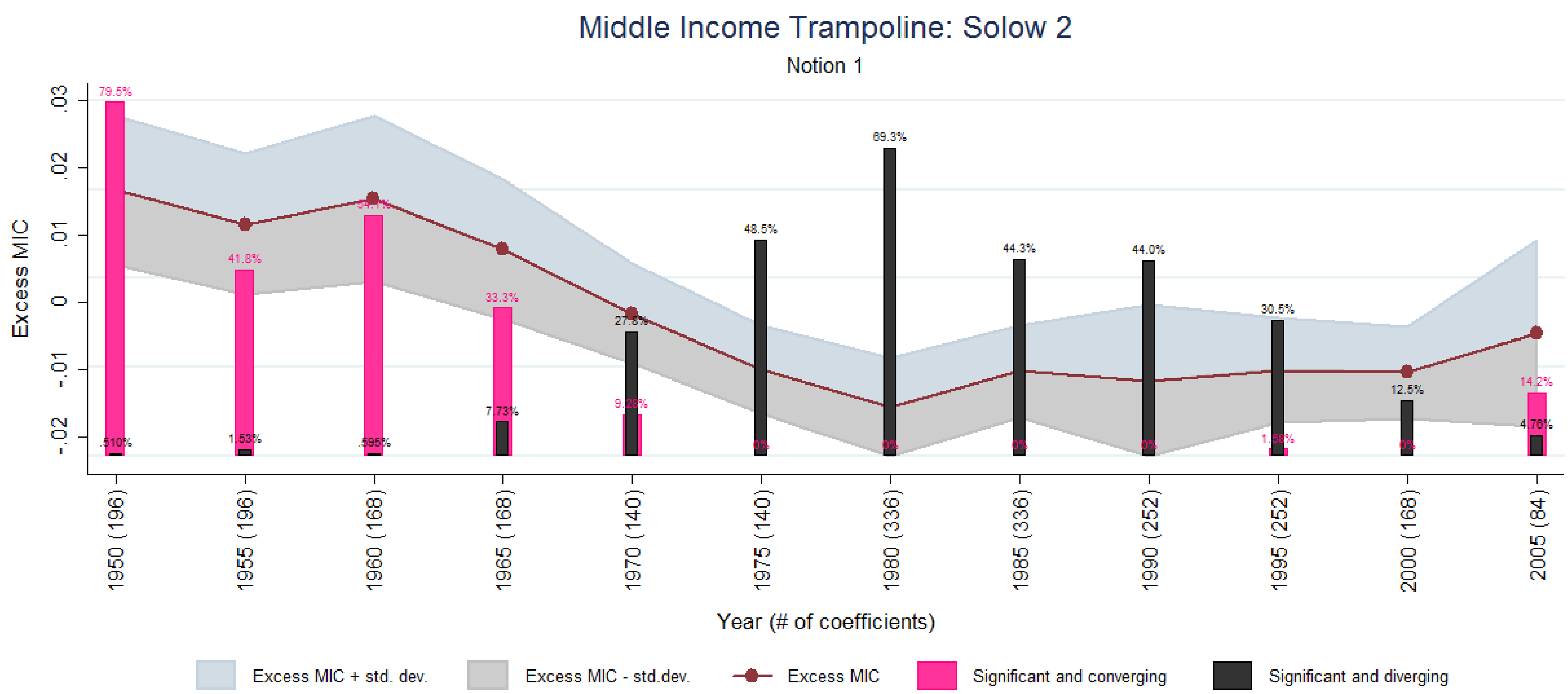
Notes: Notion 2 excludes low income countries from the sample. Significance at 10% confidence. Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and smaller nations.

Solow 2 Notion 1

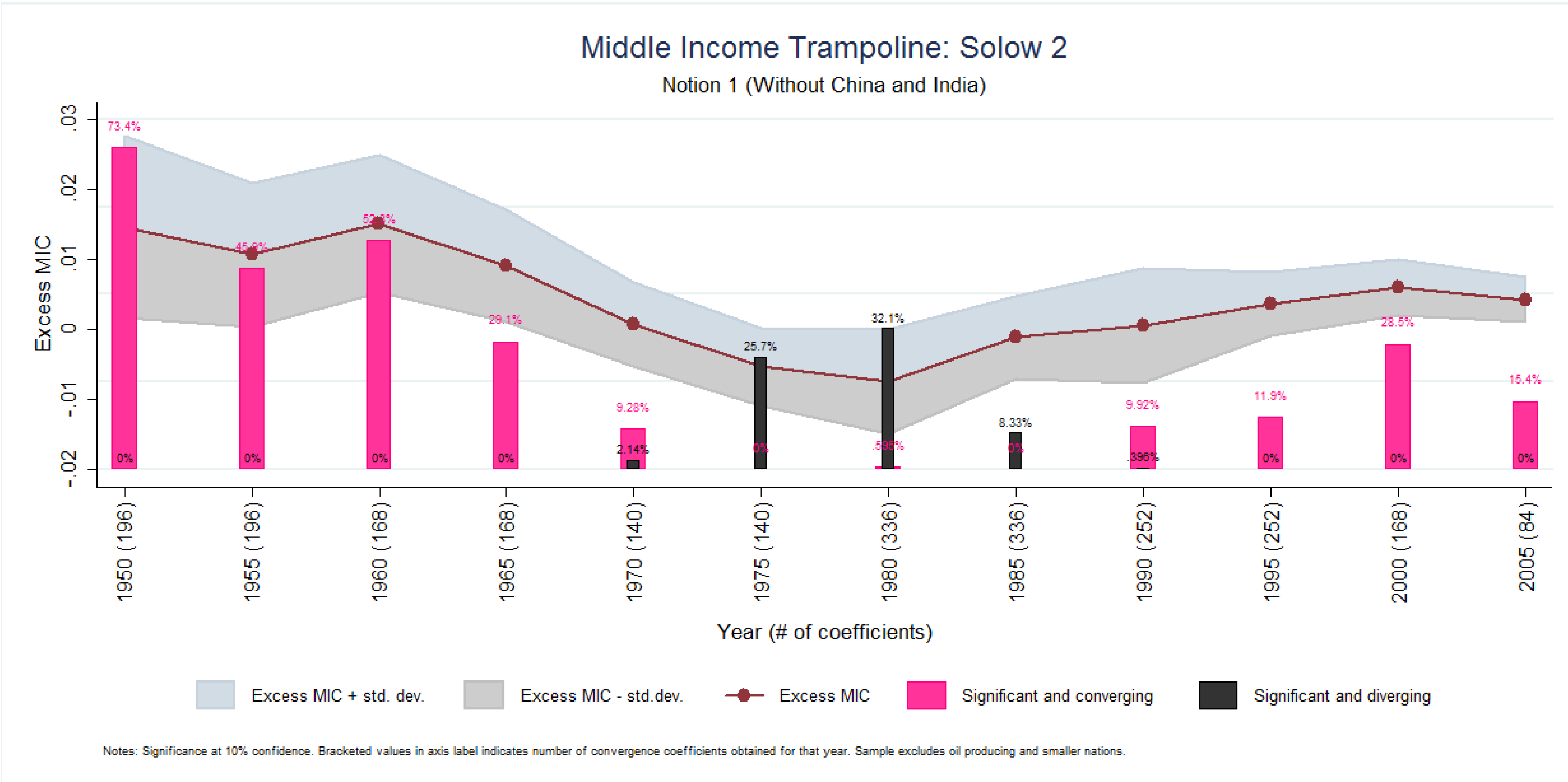
Is there a middle income trap at the level of people? The Figures below plot the results. Here we have defined a middle income person as someone whose income ranges between 15 percent and 50 percent percent of the median income in the United States (see Data Appendix for details)

In Solow 2, notion 1 we assume away the distributional impacts and check if middle income countries are growing faster than low or high income countries. At first glance, the results of notion 1 with samples including China and India suggest strong divergence in the later periods of our sample. However, China and India have been classified as low-income countries here based on the methodology outlined in Data Appendix, which seems to drive this divergence result. Evidence of this is the fact that explicitly excluding China and India from the samples results in fewer middle income dummies that are negative and significant. Thus, exclusion of these countries is a solid rejection of the middle income trap.

Figures 10(a) and 10(b)



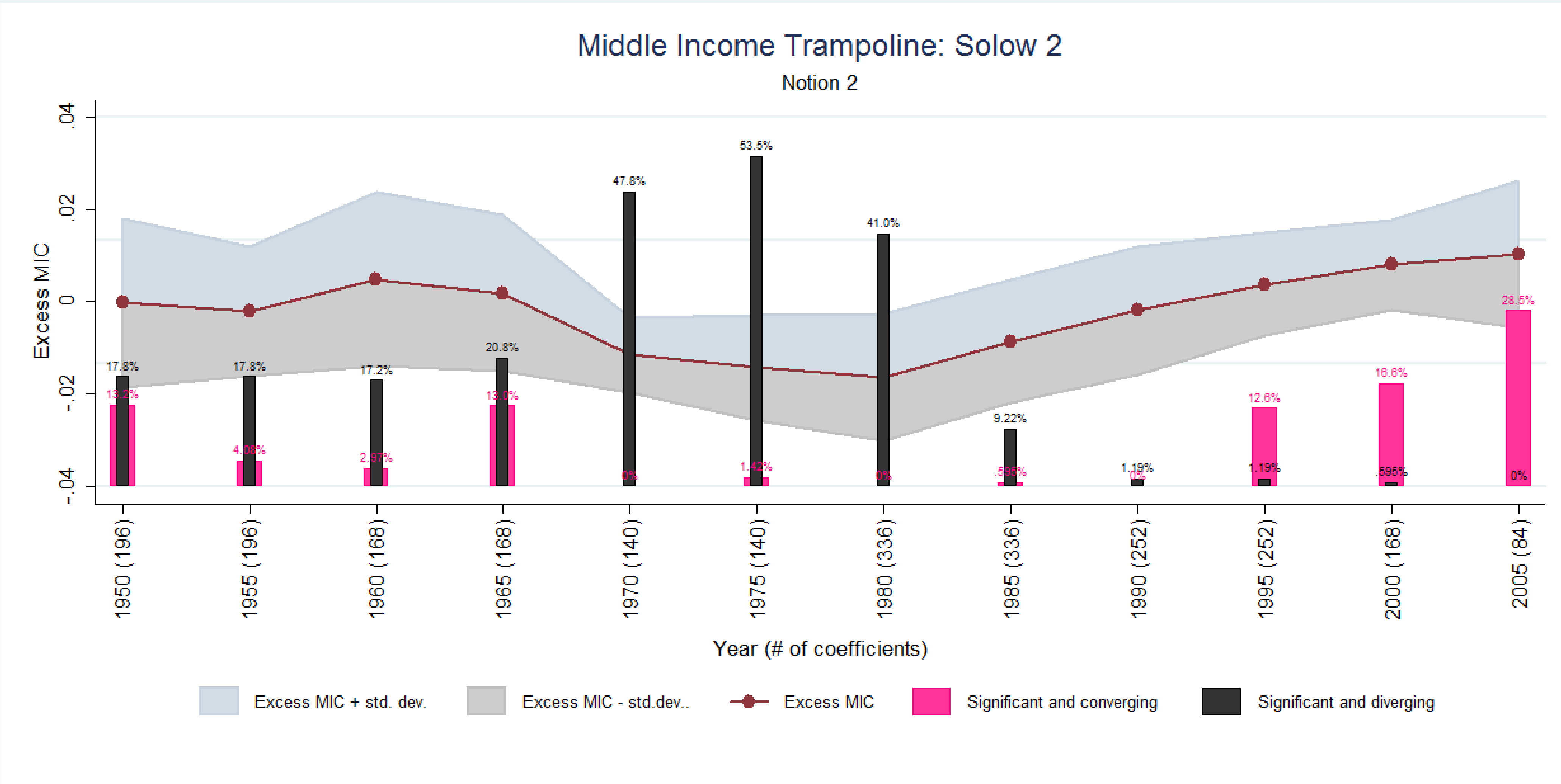
Notes: Significance at 10% confidence. Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and smaller nations.


Middle Income Trampoline: Solow 2
Notion 1 (Without China and India)
Excess MIC
.03
.02
.01
0
-.01
-.02
73.4%
29.1%
9.28%
2.14%
25.7%
32.1%
8.33%
9.92%
.396%
11.9%
28.5%
15.4%
0%
1950 (196)
1955 (196)
1960 (168)
1965 (168)
1970 (140)
1975 (140)
1980 (336)
1985 (336)
1990 (252)
1995 (252)
2000 (168)
2005 (84)
Year (# of coefficients)
Excess MIC + std. dev.
Excess MIC - std.dev.
Excess MIC
Significant and converging
Significant and diverging
Notes: Significance at 10% confidence. Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and smaller nations.

Solow 2 Notion 2

In Solow 2 Notion 2, we exclude all low-income countries from the sample. This includes China and India, as a result of which the strong convergence results are observed in the results below.

Figure 11

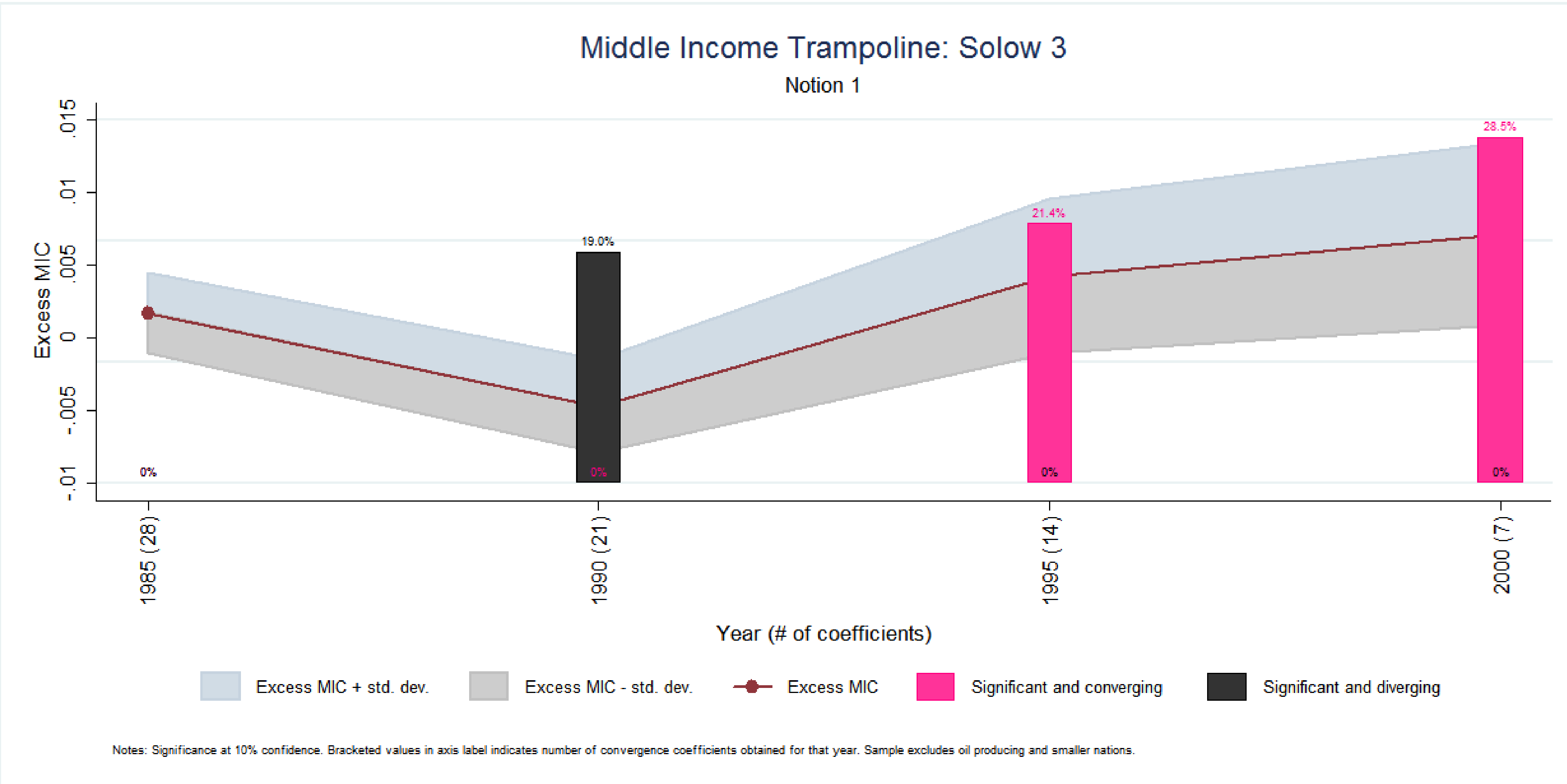


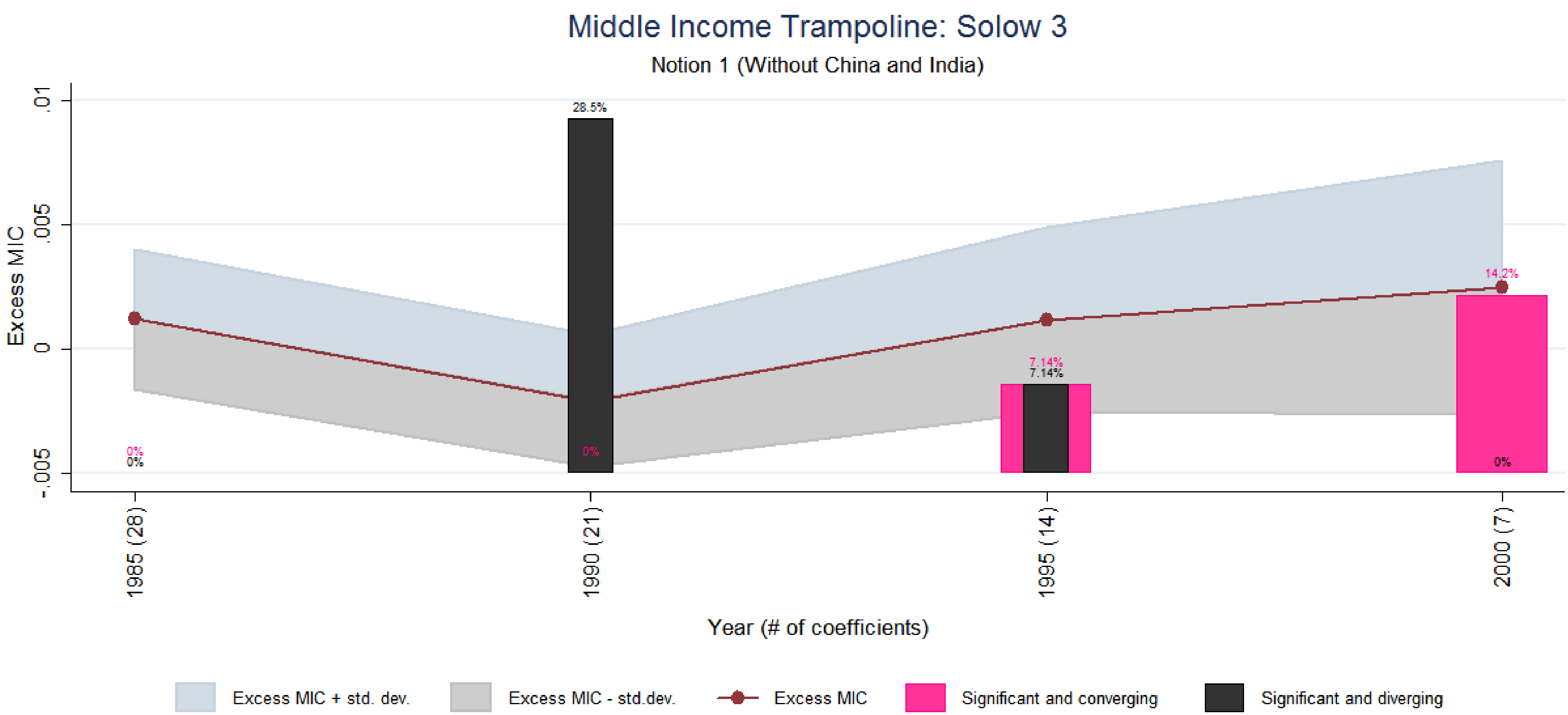
Solow 3 Notion 1

In Solow 3 Notion 1 we explore Middle Income Traps from the point of view of country wise income distribution.

In the sample with China and India, there does not seem to be a MIT. After 1995, there are only cases of positive and significant dummies. Even before that, there are few instances of negative and significant dummies (14 percent in 1990). In the sample without China and India, there are fewer instances of positive and significant coefficients but there are also fewer cases of negative and significant coefficients. Overall, the evidence points clearly to the absence of the MIT.

Figures 12a and 12b: Is there a Middle Income Trap at the level of people in all countries?



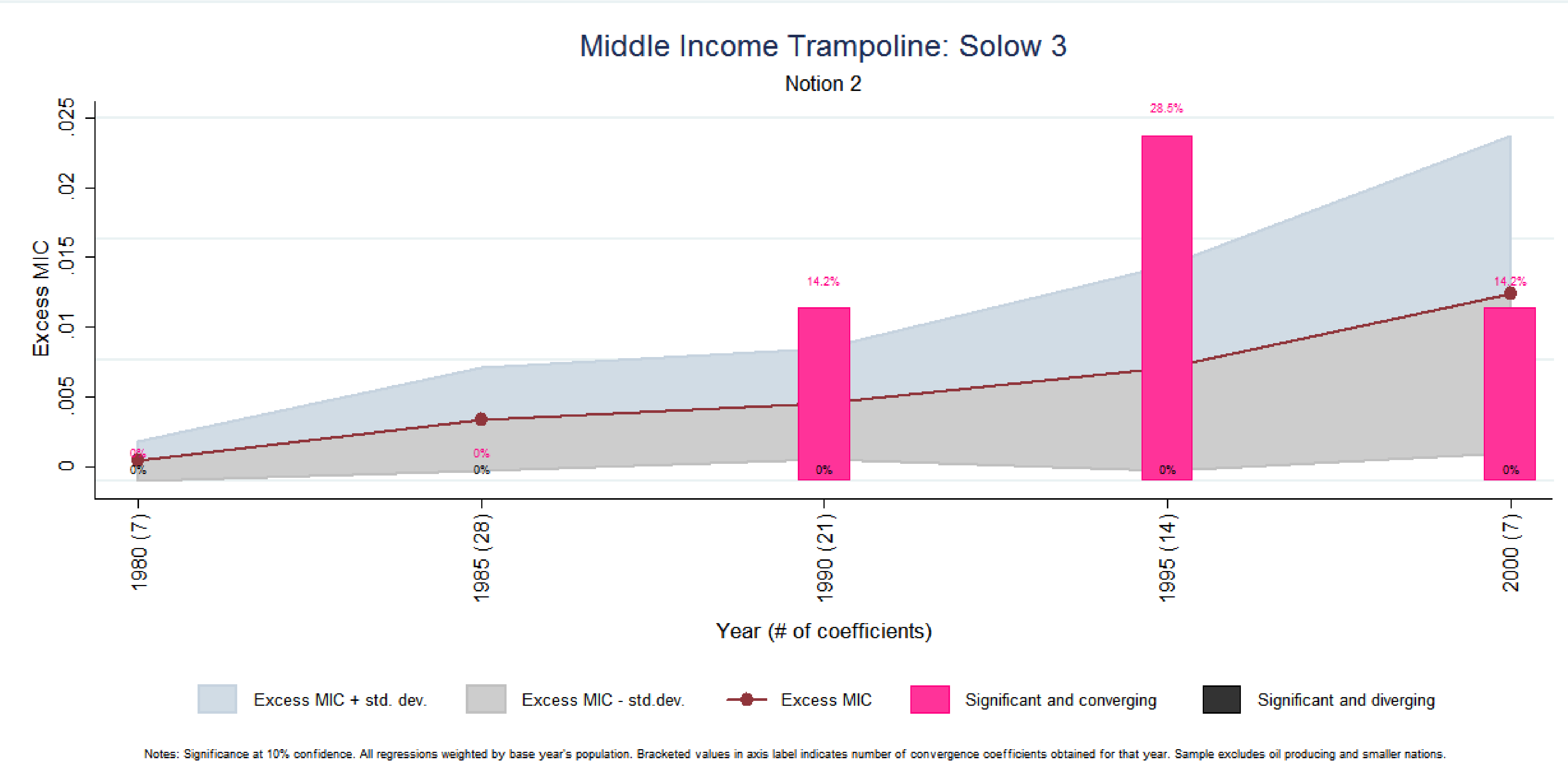


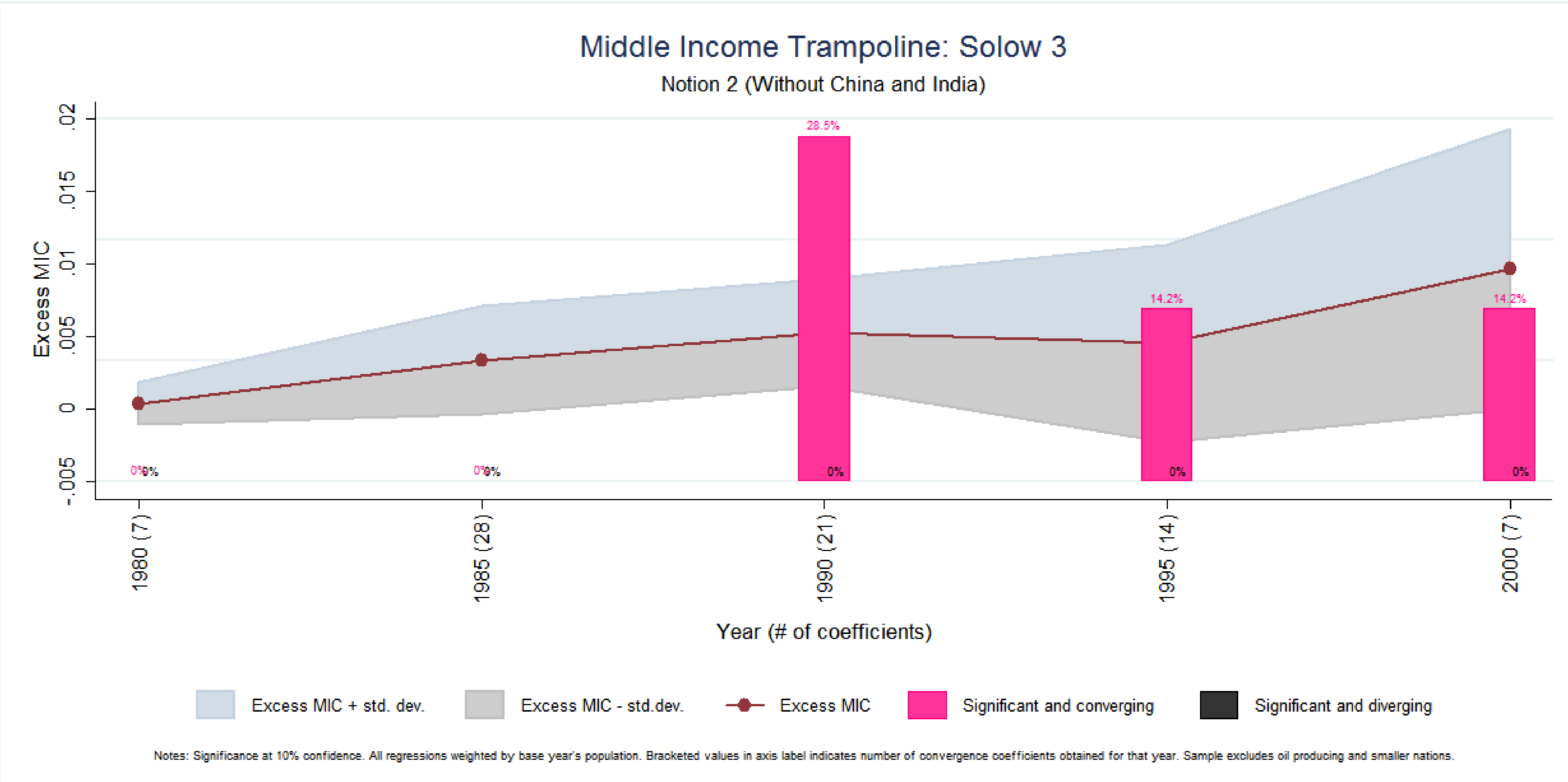
Notes: Significance at 10% confidence. All regressions are weighted by base year's population. Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and smaller nations.

Solow 3 Notion 2

Restricting the sample just to MICs and ACs, Figures 13a and 13b portray a similar picture of the lack of a MIT. The proportion of negative and significant dummies are relatively small and generally restricted to the period before 1995. Dropping China and India from the sample, of course, increases the number of negative and significant dummies and also decrease the number of positive and significant dummies. Overall, though, both instances are relatively few. Recall that only if there is a preponderance of cases of negative and significant dummies is there evidence of a MIT.

Figures 13a and 13b: Is there a Middle Income Trap at the level of people in all countries?





Middle Income Trampoline: Solow 3
Notion 2 (Without China and India)
Excess MIC
-.005
0
.005
.01
.015
.02
28.5%
14.2%
14.2%
0%
0%
0%
0%
0%
0%
0%
1980 (7)
1985 (28)
1990 (21)
1995 (14)
2000 (7)
Year (# of coefficients)
Excess MIC + std. dev.
Excess MIC - std.dev.
Excess MIC
Significant and converging
Significant and diverging
Notes: Significance at 10% confidence. All regressions weighted by base year's population. Bracketed values in axis label indicates number of convergence coefficients obtained for that year. Sample excludes oil producing and smaller nations.

VI. Conclusion

There was a brief window of optimism about the prospects of developing countries in the new millennium until the mid-oughties. Apart from that, the narrative has been one of relative pessimism.. This paper has attempted to dispel that gloom by documenting some important facts about the past. These can be summarized as follows.

Since about the mid-1980s and until 2015, there has been convergence with a vengeance. Our dating of the beginning of phenomenon is at least 10 years earlier than what is conventionally believed. The Solow framework has obscured a more simple perspective on convergence, which we call Wilde Convergence. In this perspective, we find that more developing countries (and more people in developing countries) have been catching up with their advanced country counterparts and at a much faster pace than in previously recorded history. For example, already in 1985, nearly 45 percent of countries were catching up with the US at a rate of about 1.6 percent per year; by 2015, nearly 85 percent of countries were catching up at a rate of 2.7 percent per year. At the level of people, nearly 90 percent of humanity was converging to living standards in the US at a rate of about 2 percent and by 2015, this rate had accelerated to 4.3 percent.

Another dimension of the gloomy narrative was captured in the notion of the Middle Income Trap. But we find little evidence of that. We clarify that the MIT has at least two possible meanings and can be tested in two ways: the first is that middle income countries start growing slower than the average country conditional on their level of income. A second is that while it may be easy to become a middle income country, it is difficult to move beyond it. We test both these notions and do not find evidence for them.

One feature of our analysis is that we establish the robustness of our results to a variety of data sources, time horizons, timing, and definitions of middle income. To our knowledge, this is the first paper to establish unconditional convergence (using a new metric of measurement) and refute the notion of a MIT in a robust manner.

Today, there is, once again, growing gloom about the prospects of developing countries and the possibilities of their catching-up with advanced countries (World Bank 2016, Cowen, 2016, and Rodrik, 2016). Obviously what happens in the future awaits further research. But this pessimism can be overdone. The current pessimism is driven by two factors. First, that the era of cheap capital and cheap commodities is over and second the slowdown in advanced countries both of which are believed to depress developing country prospects going forward. But cheap capital and cheap commodities were never positive drivers of long-run growth. In fact, the balance of evidence has always suggested that capital flows to developing countries were either negatively related to growth (Prasad, Rajan and Subramanian, 2007) or uncorrelated with it. Similarly, the voluminous literature on the resource curse (Ross, 1999) suggests at best a non-malign effect of commodities on long run growth. In relation to capital and commodities, the cycle and short-term have misleadingly influenced perceptions about the long run. In fact, it is during the downturn created by capital flight and loss of revenues from commodities that countries are often forced to undertaking important reforms.

Turning to the other source of pessimism, it is true that slowing advanced country growth tends to affect developing country growth via its impact on trade and exports, but again in the long run, convergence tells us that the fortunes of poorer countries depend on what they do not on what other countries do. Of course, all bets are off if rich countries succumb to a bout of dramatic protectionism a la the 1930s and choke off developing country exports. But as long as something close to current levels of openness can be maintained, developing country growth will not be unduly constrained by external factors.

Above all, pessimism must be reined in because of the recent historical record documented in this paper and the underlying reasons for it. The fact that catch-up appears to have become more ubiquitous means that more and more countries are putting in place the basic conditions that allow faster growth to be realized. Two of those conditions are worth mentioning. First, the conviction that macroeconomic stability is a necessary condition for growth seems to be spreading. In a sense, if Paul Romer's (1994) emphasis on the role of ideas in growth is correct, one such idea that has taken hold is the need for and ability to deliver macroeconomic stability, and a recognition that the failure to realize this stability lay behind the low and volatile growth performance of Latin America and sub-Saharan Africa in the 1980s and 1990s. The fact that a number of low-income countries survived the crisis of 2008-09 with minimal damage is in part a tribute to the embrace of the idea of macro-economic stability.

A second condition seems to be the spread of new information and communication technologies, whose transformational role in low-income countries is now being realized. Neither of these conditions is a guarantee that low-income countries will grow at Chinese rates of growth in the future. What they do suggest is that on balance, more countries will catch up rather than lag behind the frontier in the years ahead.

A third factor that seems to have come into play is what might be called a "growth begetting growth" dynamic. If countries grow for some period of time, growth itself seems to create positive change, reinforcing subsequent growth.

Finally, it must be remembered that even after two decades of convergence, disparities remain considerable. India's GDP per capita (PPP) is about 11 percent of that of the US; Sub-Saharan Africa's star performer, Rwanda's is about 3 percent. The advantages of backwardness—or the distance from the frontier--will remain for a considerable time which should allow the convergence process to unfold given the actions that countries are undertaking.

But for now, the recent historical record needs to be better understood; and that record is one of something unprecedented at least since the industrial revolution. We perhaps over-dramatize when we speak about glimpsing the end of economic history. But what has happened since the 1980s is worthy of dramatization given the repudiation of a long and pessimistic history.

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Appendix 1: Description of Data and Methodology

The paper makes use of the following main datasets:

1/ Penn World Tables (8.1)
2/ World Development Indicators (April-2014 vintage)
3/ Maddison Tables
4/ PovcalNet (2005 PPP adjusted international dollars)
5/ Lakner-Milonavic World Income Dataset
6/ Luxemburg Income Study

The first step for PWT, WDI and Maddison is to extend these datasets to 2015. We do so by using IMF's World Economic Outlook (October 2014 vintage) and compounding the growth rates for 2013, 2014 and 2015 to the 2012 GDP per capita of the all countries in the respective datasets. The corresponding population data for 2015 was obtained from United Nations' Population Division. Next, we keep all quinquennial years starting 1950 (or 1980 for WDI) up to 2015 and drop others. We calculate all possible 10, 15, 20, 30, 40, 50 and 60 year growth rates for each of these years in the dataset. The growth rates are calculated on a compounded annual growth rate (CAGR) basis, defined as:

$$Growth\ rate_{t_1,t_0} = \left(\frac{y_1}{y_0}\right)^{\frac{1}{t_1 - t_0}} - 1$$

Relying on World Bank's classification of economies that are deeply dependent on oil and gas commodities we exclude these countries from our datasets. We also drop countries with population less than 1 million in the year 2010. Next, we create the middle and low income classifications for each country-year tuple, comparing the country's GDP per capita (in 2005 PPP dollars constant terms everywhere) to US' GDP per capita for that year. We construct a middle income dummy for k1-k2 percent of US GDP, where k1 is in {15, 20} and k2 in {35, 40, 45}. Similarly, countries are classified as a low-income dummy if their GDP per capita is lower than the 15 percent or 20 percent of US' GDP per capita. We also use World Bank's definition of middle income countries, resulting in a total of 7 possible definitions of middle income country.

Finally, to ensure that our results are not driven by the samples specific to individual datasets, we also run our regressions on common samples. These common samples consist of country-year tuples that were common to WDI, Madison and PWT, comparing each dataset—two at a time and three at a time. We then ran our tests on each dataset restricting ourselves to these common tuples only. All results from individual datasets, samples common to two datasets at a time and three datasets at a time were then pooled and the combined regression coefficients have been reported in the Figures in the main text.

In Solow 1, we run our baseline unconditional convergence equation for all three types of samples, datasets and growth rates for each quinquennial years. Following Lakner-Milonavic, for Solow 2, the coefficients are obtained by weighing the regressions using total population of the country as analytical weights.

In Wilde 1, we calculate broadening by finding the proportion of countries in the sample that are growing faster than the United States in that quinquennial year. Speed in Wilde 1 is the difference between the growth rate in GDP per capita of all countries and that of the United States. In Wilde 2, speed is calculated by weighing the GDP per capita by the population of the country. Similarly acceleration in Wilde 1 is calculated by restricting ourselves to countries that are growing faster than the US and in Wilde 2 by finding the difference between GDP per capita weighted by a country's population and the US, conditional on the fact that the country is, weighted by its population, growing faster than the US.

Solow 3: Unconditional Convergence and Middle Income Traps

Studying the distributions of income per capita under Solow 3 is empirically more complicated than Solow and Wilde 1 and 2 due to issues pertaining to comparability of surveys across countries, ICP comparison between countries, income and consumption surveys, difference between survey means and national income accounts, separate rural and urban distributions for some countries, difference in spatial consumption deflators across countries, etc. (Ferreira, Francisco H. G.; et all, 2015 for a most recent survey of all of these issues). In order to stay consistent with earlier studies on this topic and keep our results comparable to these earlier works, we do not innovate in terms of treating different sources of data differently and process the data in the spirit of Lakner-Milonavic (2015). The main steps are outlined below:

1. To start, our POVCAL dataset has 1196 country-year observations (including Urban, Rural and weighted country distributions). We drop off the observations with missing shares, Montenegro and Kosovo and income surveys from countries that conducted both income and consumption surveys in the same year (Mexico). This was merged with survey means from POVCAL and missing survey means were dropped.
2. Next, urban distributions were merged with the overall country distributions for Ecuador, Honduras, Argentina, Micronesia and Uruguay. Only three countries remained in the dataset with a separate rural and urban distribution—India, China and Indonesia. Following, Lakner-Milonavic (2015) (LM 2015), the aggregate country distributions (weighted Lorenz curves) were dropped for these three countries.
3. The reference years (1985, 1990, 1995, 2000, 2005 and 2010) are created next. Any survey year that was 0, 1 or 2 years away was classified as one of the reference years. The classification is in the order of the distance of the survey year from the reference year—that is, a 0 year difference is allocated the reference year before a one year survey, a one year survey is preferred to a two year survey or otherwise we stop at two years. This step is slightly different from LM 2015, who use the same classification but also drop POVCAL surveys that are 3-7 years away from their reference year. This is to ensure that their five year growth periods reflect close to five year survey intervals. In our case that restriction is less applicable since we are looking at atleast a 10 year growth rate.
4. We also drop oil countries from the data set and from prior knowledge drop the 2009 consumption survey from India and classify the 2011 survey as the 2010 reference survey (Deaton, 2011). As earlier, we also drop small countries (with population less than 1 million in the reference year 2010) from our dataset.

5. Having constructed our reference years, we address survey years that are equi-distant from our reference year (example: both 1998 and 2002 survey will be classified as 2010 reference year and both are 2 years away from the reference year). We follow two rules here: (1) for a given country, we choose either an income or consumption surveys based on whichever occurs more often than the other; i.e., we keep only consumption (income) surveys for the country in our dataset if they occur more frequently than the income (consumption) survey (as a result, we remain consistent with LM,2015 strategy of keeping either consumption or income survey for a country) (2) we keep the lower of the two years contending for the same reference year (in the earlier example, 1998 would be included and 2002 will be dropped for the reference year 2000, if both were the same type of survey (if not, they would be addressed in step(1)).
6. For LM-WPID dataset, we first find the income/consumption in a decile as a percentage of the total income/consumption of all individuals the survey (share of decile = RRinc*10/RRmean). Before proceeding further, I drop the POVCAL and LIS data in LMWPID datasets as we are creating these datasets separately. As in POVCAL, small nations and oil countries are excluded from the dataset. Construction of reference years and classification of survey years into reference years follow as (3) above and equidistant survey years are included using the two rules outlined in (5) above. We make one exception to the reference year construction, however. We classify the India-1997 rural and urban surveys as 2000 to allocate one extra reference year to India. We do this because India has a 1993 survey and a 1997 survey and no other surveys in the two year vicinity of reference year 2000. Not making this one year adjustment to the rule would exclude India from 2000 reference year based growth rates and therefore exclude a large percentage of the world population from our analysis.
7. For LIS, we drop the household equivalent mean per capita income measure because it adjusts for household level economies for scale. We drop survey years below 1985 to keep our time horizon comparable with POVCAL and LM-WPID datasets. Small countries and oil based economies are excluded as for other datasets. Construction of reference years and classification of survey years into reference years and treatment of equidistant survey years follow the same rules as above.
8. In the next step, we merge the three datasets. This expectedly causes duplicate country-survey year tuples to emerge in our dataset. We remove the duplicates by giving samples from LM-WPID precedence over POVCAL and LIS, and choosing POVCAL over LIS for competing duplicate observations. The net effect of this step is that we are able to extend LM 2015 to updated POVCAL data and adapt their rules to our reference years and growth rates.
9. Following the same classification for middle income status as earlier, we compare a country's decile-year income per capita to the income per capita of the fifth decile in US at the same reference year, checking for k1={15 percent, 20 percent} and k2 ={35 percent, 40 percent, 45 percent}. We allow for some flexibility in the middle income status for consumption based surveys by changing the k1 = {10 percent, 15 percent} and k2 ={30 percent, 35 percent, 40 percent}. This is because for these surveys we are comparing the *consumption* of a country decile to the *income* of the fifth decile in the US.

10. Finally, the growth rates are calculated for 10, 15, 20 and 25 year periods. In creating these growth rates, we preserve the distance between survey years. For example, consider survey year 2008 (classified as reference year 2010). To calculate the 10-year growth rate, we first look for the survey year 1998. If we find the survey year 1998 for the given country-decile, we calculate the growth rate and stop our iteration. If the 1998 survey year is not found, we look first for a survey in 1997 and stop. If that too is unavailable we look for 1999 survey year, then 1996 and finally 2000. Thus, in the "worst" case we classify a 1996-2008 (12 years) or 2000-2008 (8 year) as a 10-year growth rate for the reference year 2010 (the only exception here as noted earlier will be the India 2011-2004 survey pairs for reference year 2010 which has been classified as a ten year growth rate but are in fact a 7-year growth rate).

Appendix 2: Robustness of Results on Wilde Convergence to an Alternative Choice of the Economic Frontier

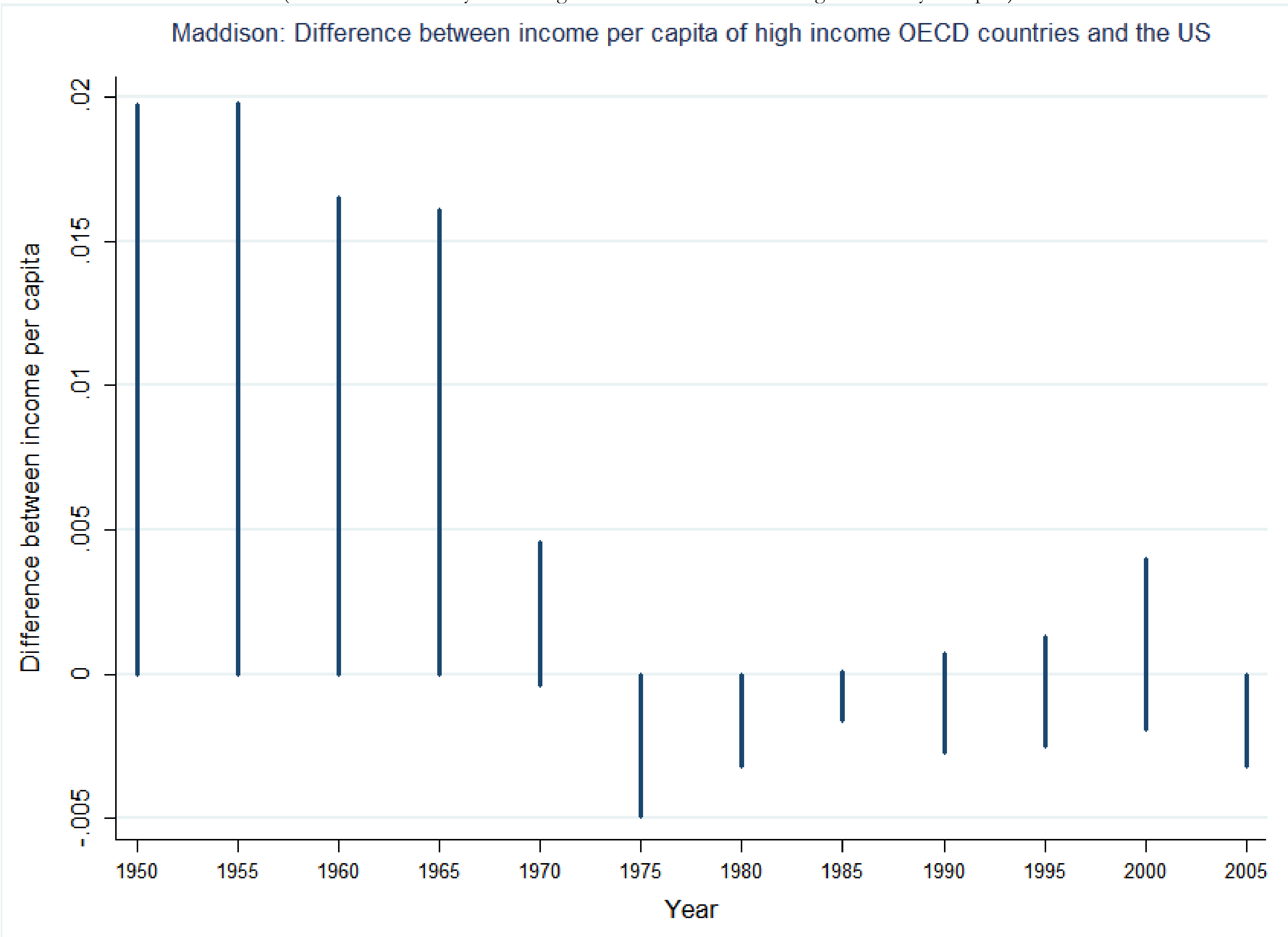
One potential criticism for our Wilde measures of unconditional convergence could be that our comparison of a developing country growth rate is made with respect to United States (which serves as an indicator of the world's economy frontier in our analysis) rather than countries such as OECD-High Income[5]. As noted earlier, our choice of US as the world's economy frontier is driven by the fact that we wanted a consistent measure of world income frontier for all years between 1950 and 2015. Using the OECD-High Income country classification would have been an inconsistent measure of the frontier because countries such as Japan (or Mexico, Korea, Chile, etc.) were low-income countries in 1950-1960 and therefore would have grown much faster than high-income countries during that period. This trend becomes clear if we plot the difference between the average growth rate of GDP per capita of high-income OECD countries and the US growth rate over 1950-2005 in the Figure 14 below.

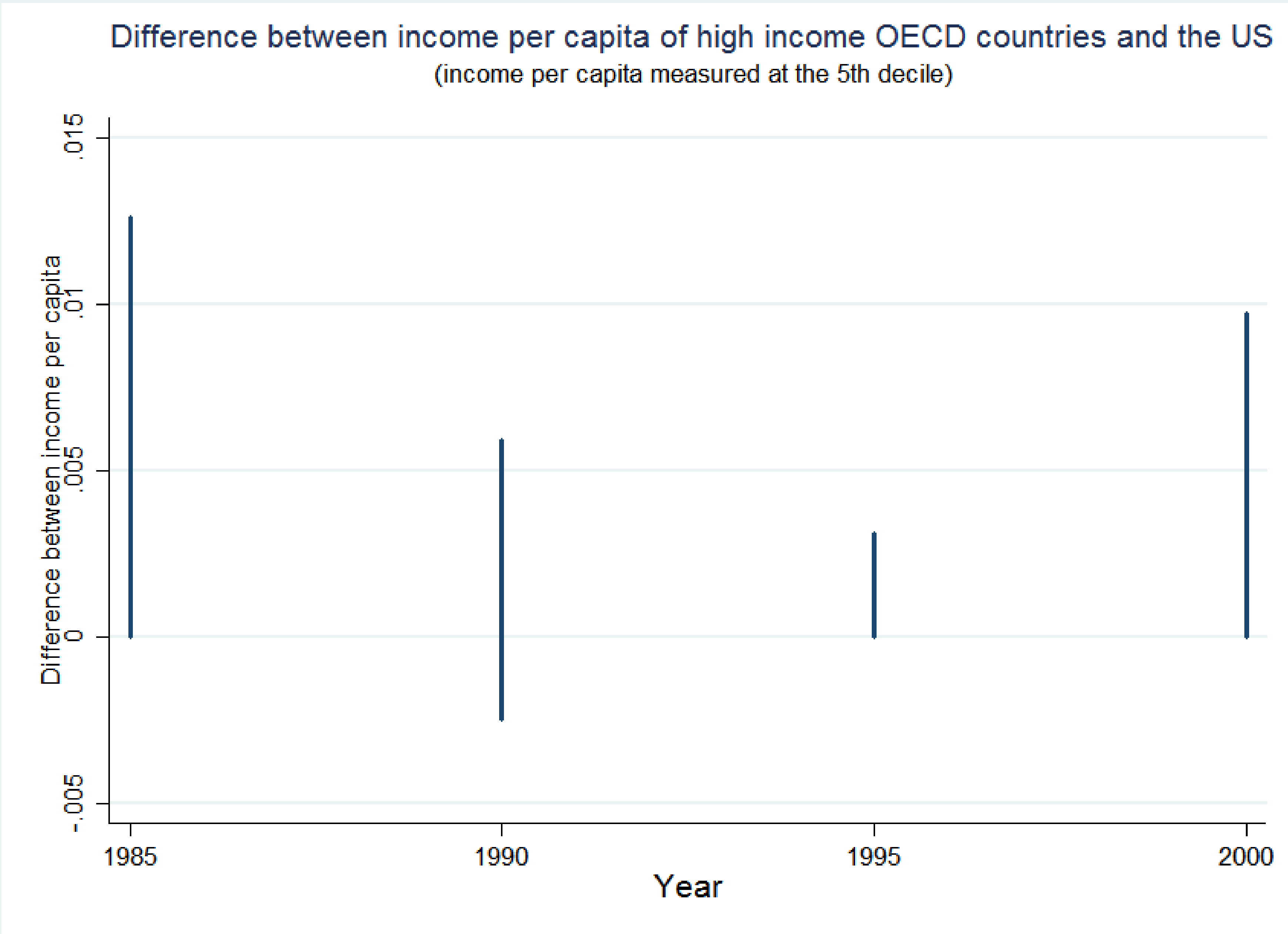
Figure 14a and 14b show that the difference in average per capita GDP of the country (or of the 5th decile in the country) and that of the US is high during the periods when several of the current high-income OECD countries were graduating into their eventual high income status. Moreover, at least for the period when strong convergence has been noted repeatedly (post-1990), the difference in GDP per capita growth rate for the OECD: High income and the US is negative—that is, if we used the OECD averages as the frontier definition, we would have obtained ever greater speed, broadening and acceleration for all years after 1990. The same is true for the distributional analysis conducted in Wilde 3: if we used our OECD high income averages in lieu of US 5th decile growth rates, we would have reduced our speed of convergence by factors of 0.5 percent, 0.25 percent and 1 percent for 1990, 1995 and 2000. The effect of this reduction would be small because the speed, acceleration and broadening for these years in Wilde 3 are currently: (1.68 percent, 1.68 percent, 3.79 percent), (2.13 percent, 2.31 percent, 4.25 percent) and (83.93 percent, 79.12 percent, 92.16 percent) respectively.

[5] The list of countries included in this group are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, New Zealand, Portugal, Spain, Sweden, Switzerland and United Kingdom

Figures 14a and 14b: Difference in growth rate of income per capita between OECD countries and the US

(the band is created by calculating the differences at different lags and base-year tuples).





Difference between income per capita of high income OECD countries and the US
(income per capita measured at the 5th decile)
Difference between income per capita
-.005
0
.005
.01
.015
1985
1990
1995
2000
Year