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When Will Global Gender Gaps Close?

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When Will Global Gender Gaps Close?

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ABSTRACT: On the current pace of reforms, global gender gaps are estimated to close, using deterministic (linear or log-linear) trends, over the next three centuries. This means that many women will likely not be able to fully use their abilities and talents, to the detriment of societies, for a long time. Yet this paper shows that, absent a significant step up in policy efforts, gender gaps may in fact never close. Using Markov chains, a common approach in macroeconomics, this paper analyzes the dynamics of the cross-country distribution of the gender gap in labor force participation. This methodology does not impose strong restrictions on the data, allowing for episodes of progress as well as regress by countries on gender inequality. Based on the experience of the past three decades, the analysis predicts a further narrowing of gender gaps over time. But the long-run distribution of gender gaps in labor force participation features a substantial share of countries with persistently large gaps, implying that—absent a strengthened and systematic policy effort—some of the current misallocation of women’s talents and abilities could persist perpetually.

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I. Motivation

Earlier this year, the UN Secretary General stated, “*Gender equality is growing more distant. On the current track, UN Women puts it 300 years away...*” Extrapolating the rate of progress from 2006 to 2023, the World Economic Forum (2023) reported that closing global gender gaps in economic participation and opportunity will take 169 years, up from the pre-pandemic period. In a similar vein, based on current legal frameworks and the recent pace of reforms, the World Bank’s 2023 Women, Business, and the Law report estimated a minimum of 50 years for the closing of the gender gap in legal rights. These call for stepped up progress in closing gender gaps, not least because the global growth outlook over the next several years is the weakest in decades (IMF 2023). Better utilizing available human resources and reducing misallocation of talent and skills can help achieve stronger and more inclusive growth, benefiting women and societies.

This paper lends further support to these concerning time-to-equality calculations and to the urgent calls for intentional and systematic policy efforts to close gender gaps. Using a common approach from macroeconomic dynamics to study the evolution of gender gaps in labor force participation across countries, it presents an even more dire interpretation of the data—based on trends over the past three decades, key gender gaps may never close but could perpetually remain elevated for many countries.

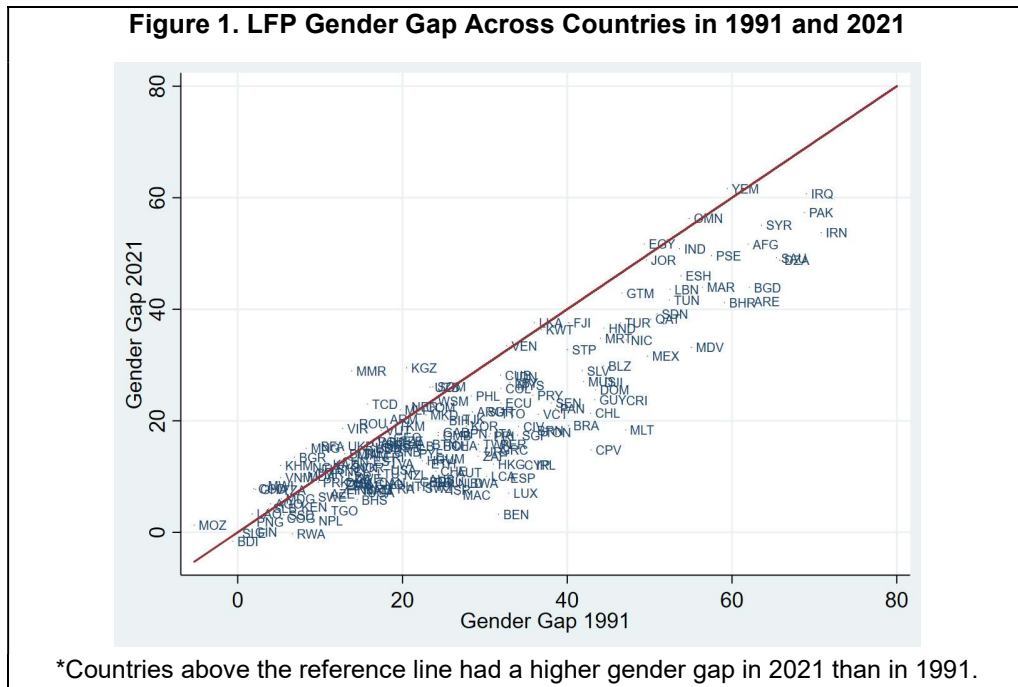
Female labor force participation (LFP) is a basic pillar of female economic empowerment. Gaps in female LFP vis-à-vis male LFP are macro critical, i.e., they impact macroeconomic growth and stability. For example, Ostry and others (2018, as updated by IMF staff) calculate that closing female LFP gaps for emerging market and developing economies would, on average, raise real GDP by 22–23 percent. This constitutes a potentially important engine of growth, complementing the benefits of structural reforms (IMF WEO 2019 estimates the impact of different types of structural reforms).

For 189 countries, annual data are available since 1991 on the gender LFP gap defined hereafter as the labor force participation rate for men minus the labor force participation rate for women (see Figure 1).¹ In 1991, the world’s average gap was 26.6 percent, while in 2021, the average gap was 19.5 percent, implying a reduction rate of 1.03 percent per year.

Given the importance of gender gaps in LFP, one might use the narrowing of the world’s average LFP gap observed from 1991 to 2021 to infer the pace at which the gap will continue to close. For instance, if the gap were to continue to fall at the observed rate of 1.03 percent per year, 99 percent of the current gap would be closed in about 445 years.² This type of calculation is at the heart of the above-mentioned common approaches regarding the time that it would take the world to achieve gender equality.

¹ The gender LFP gap can naturally vary between -100 percent and 100 percent. The data are produced by ILOSTAT from the International Labor Organization and are available at <https://www.ilo.org/shinyapps/bulkexplorer11>.

² Note that (100 percent minus 1.03 percent) elevated to the power 445 is equal to 0.998 percent. See Appendix 1 for more variations and further details of this methodology.



Underpinning such calculations, however, is a *strong implicit assumption* that all economies are on a well-defined deterministic trend toward absolute gender equality. More realistically, however, as illustrated by the data points above the 45 degree line in Figure 1, country gaps are likely to fluctuate up and down over time depending on trends, policies, and shocks. Given the pattern observed in the data, how much will country gaps fluctuate in the long run? Will country gaps fluctuate around a zero average gap? Or will they do so around a positive (or negative) average gap?

To address these questions, we follow Quah (1993), who studied output convergence across countries. Quah's (1993) approach analyzed how each country's data move over time to derive the long-run distribution across countries. The approach is based on discrete-state Markov chains and has sufficiently flexible dynamics to accommodate cross-country distributions of gender gaps that may oscillate up and down, exhibit regular cycles, become disperse over time, converge to a single point, or converge to a unimodal or a multimodal stationary distribution in the long run. The theoretical underpinnings of the approach may be found, for example, in Durlauf and Quah (1998). Such an approach allows the data to speak for itself.

The methodology differs from a linear or log-linear trend for global averages in two ways. First, it accounts for the heterogeneity in gaps across countries. Second, it allows country-level gaps to fluctuate over time, as in the data, rather than viewing the gaps as moving along a rectilinear (or log-rectilinear) trend. This allows us to focus on the evolution of cross-country distributions, rather than on the average trend of a given world index. While we do not find evidence of a bimodal long-run distribution (as Quah (1993) did for cross-country deviations from world's output per person) we find that the data on LFP gaps do not support convergence to full gender equality in the long run.

Box 1. On possible theoretical underpinnings for convergence hypothesis

In the case of output dynamics analyzed by Quah (2003), the theoretical hypothesis of deterministic output convergence for all countries is a natural result of the basic foundations of the neoclassical growth models of, e.g., Ramsey and Solow.

In the case of gender gaps, we do not have such a strong point of departure. However, in leading quantitative work by Guner and others (2011) and Bick and others (2017), among others, female LFP is partly governed by the household's tradeoff between the disutility (psychological or well-being) of female participation and the net salary of women. This disutility reflects, in a simple way, according to Bick and others (2017), the "inconvenience of scheduling joint work, home production and leisure activities, or spending less family time with children." If this disutility were invariant to economic changes outside the household, economic growth could lead to reductions in gender gaps via the overall growth of wages over time.

Equivalently, as in Malta and others (2019), under such a mechanism, increments in female education can increase women's net salary, with a similar positive impact on female participation. In related work, Heathcote and others (2010) provide a labor supply model that is symmetric across genders to measure the role of several factors, including preference shifts, on U.S. female participation. They also consider the contribution of gender wage gaps, income sharing rules, and marriage patterns in explaining the increase.

Despite its potential, we note two caveats for the analysis of long-run dynamics of gender gaps under the general approach hinted by these lines of work. First, modeling disutility or preference shifters explicitly would be a pre-requisite for theories of endogenous gender LFP gaps in the long run. Second, such theories would desirably model the mechanics of certain barriers to female LFP such as legal frameworks, social norms, and religion.

We now use Markov chains to assess the dynamics of LFP gender gaps. The next section introduces our main result through a very simple example. We then analyze the robustness of the result to several variations in the methodology and explore the joint dynamics of the LFP gender gap and the wealth of nations using a bivariate Markov chain. The final remarks conclude with an agenda for future work.

II. A Simple Yet Rousing Exercise: The Dynamics of "High" and "Low" Gaps

In 1991, 29 countries displayed LFP gender gaps below 10 percent (hereafter "low") while 160 countries displayed gaps above 10 percent (hereafter "high").³ Out of the 29 countries with low gaps, 21 were still low by 2021 while 8 of the countries had moved toward high gaps. Also, out of the 160 countries with high

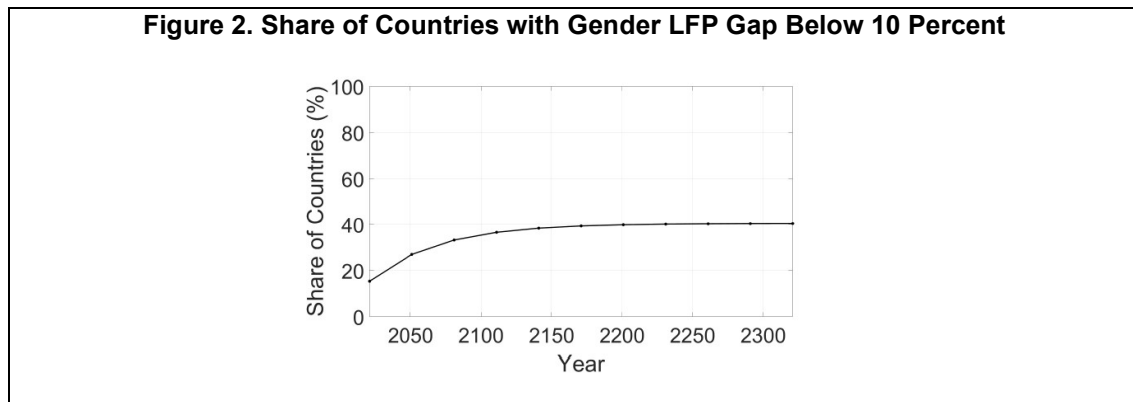
³ We define "high" and "low" based on threshold gap of 10 percentage points for the purposes of this illustrative exercise, albeit, equally, another threshold could have been chosen.

gaps in 1991, 30 countries had moved to low gaps by 2021, while the remaining 130 were still on high gaps. These transitions are the result of policies, institutional settings, shocks, and trends over the past three decades as well as the status quo of all conditions observed at the beginning of 1991.

The observed movements imply a probability of transition from low to high of $8/29$ (i.e., 27.6 percent), and a probability of transition from high to low of $30/160$ (i.e., 18.8 percent). We summarize these probabilities in the *transition probability matrix* in Table 1.

	Low Gap in 2021	High Gap in 2021
Low Gap in 1991	72.4	27.6
High Gap in 1991	18.8	81.3

What would happen if countries continued following these patterns, moving across high and low over time according to these transition probabilities? Using the mathematical properties of transition probability matrices, under the dynamics of Table 1, the total number of countries with low gaps would become 51 by 2051. By around the year 2200, the distribution of the gap would settle with a constant share of approximately 40 percent of countries in the low gap category and the remaining countries in the high gap category (see Figure 2).



That is, the dynamics implied by the above data-driven transition probability matrix do not point to a global closing of the gap. *According to this simple Markovian chain model, estimated using the broadest available data, a large share of countries will continue to display high gender gaps in LFP in the long run, assuming the dynamics of the recent past continue to shape the future.*

⁴ The first row says that, out of the countries that had low gaps in 1991, 27.6 percent will move toward high gaps while the rest (72.4 percent) will remain low. The second row says that, out of the countries that had high gaps in 1991, 18.8 percent will move toward low gaps and 81.3 percent will remain with high gaps. These probabilities inform the dynamics of the gender gap.

The dynamics between 1991 and 2021 are thus insufficient to ensure a sustained or rapid transition to female economic empowerment.⁵ On one hand, the movement of the distribution is very slow while, on the other, the long-run distribution contains a high share of countries with high gaps. At these assumed rates of change, the dynamics of gender gaps settle on a steady state in roughly 200 years, but without any evidence in favor of a global closing of the gender gap.

The long-run share of low-gap countries depicted in Figure 2 depends positively on the probability of high-to-low transitions and negatively on the probability of low-to-high transitions.

Mathematically, in this framework, a closing of the gender gap would require a zero low-to-high transition probability. In such case, the “low” gap state would be *absorbing*, and all countries would eventually end up with “low” gaps. This assumption of a zero low-to-high transition probability is, more precisely, the strong and highly restrictive assumption underlying prevalent time-to-equality calculations. But the data indicate a transition probability from low to high that is close to 30 percent.

While illustrative, the exercise shown above could be seen as too simplified. First, we only used the data of two years (1991 and 2021). Second, we split the range of possibilities into only two categories “high” and “low”. In the following section, we explore more flexible specifications of the exercise and provide more granular results for the possible evolution of the distribution of the global LFP gender gap. We also explore how the dynamics have changed over time and how Covid-19 affects the results. In summary, across all the variations considered, the main conclusion remains robust: *the current dynamics of the LFP gender gap across countries imply elevated gaps in the long run for a large share of countries.*

III. The Evolving Global Distribution of the Gender LFP Gap

This section extends the results of the previous section to four settings. It allows us to provide further detail on the possible evolution of the global distribution of the gender LFP gap, assuming continuation of recent policies and patterns of shocks and trends into the future.

We organize our investigation into three inter-related questions: (i) how robust is our result to sample selection and other aspects of the methodology? (ii) what are the dynamics of the middle- and high-end of the world distribution of the gap? and (iii) how have the dynamics changed over the 1991–2021 period? To answer these questions, we consider four variations of the theme from the previous section.

First, to tackle question (i), we calculate transition matrices using our full sample (1991 to 2021) at annual, five-, and ten-year frequencies. This means that we examine one, five-, and ten-year transition probabilities instead of just the 30-year transition probabilities shown in the previous section. We also reproduce all results excluding the years 2000 and 2021 to purge the effects of COVID-19 and,

⁵ One prominent example is the United States, where a gap between 10 and 20 percentage points has held since 1990, despite a marked reduction in male labor force participation. See Blau and Kahn (2013) for an early investigation of the causes of this deceleration.

additionally, in Appendix 3, address potential concerns of measurement error by adding population weights to the methodology.

To answer question (ii), throughout all variations, we use the finer granularity of an eight-category distributional model. Given the substantial increase in the number of observations owing to our focus on higher frequency transitions, we can split the global range of gender gaps into these eight categories (instead of the two categories earlier)—the gap category cutoffs are the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the sample distribution. We also employ a nonlinear interpolation technique to plot the evolution of several percentiles of the gap over time. The specifics of this technique are described in Appendix 2, which helps us to illustrate the evolution of the underlying distribution in a simple manner.

To answer question (iii), we compare the results from the first 15 years of data in our sample versus only the most recent 15 years of data. This exercise provides a notion of whether the movement of the distribution toward a more equitable gender gap is accelerating or decelerating.

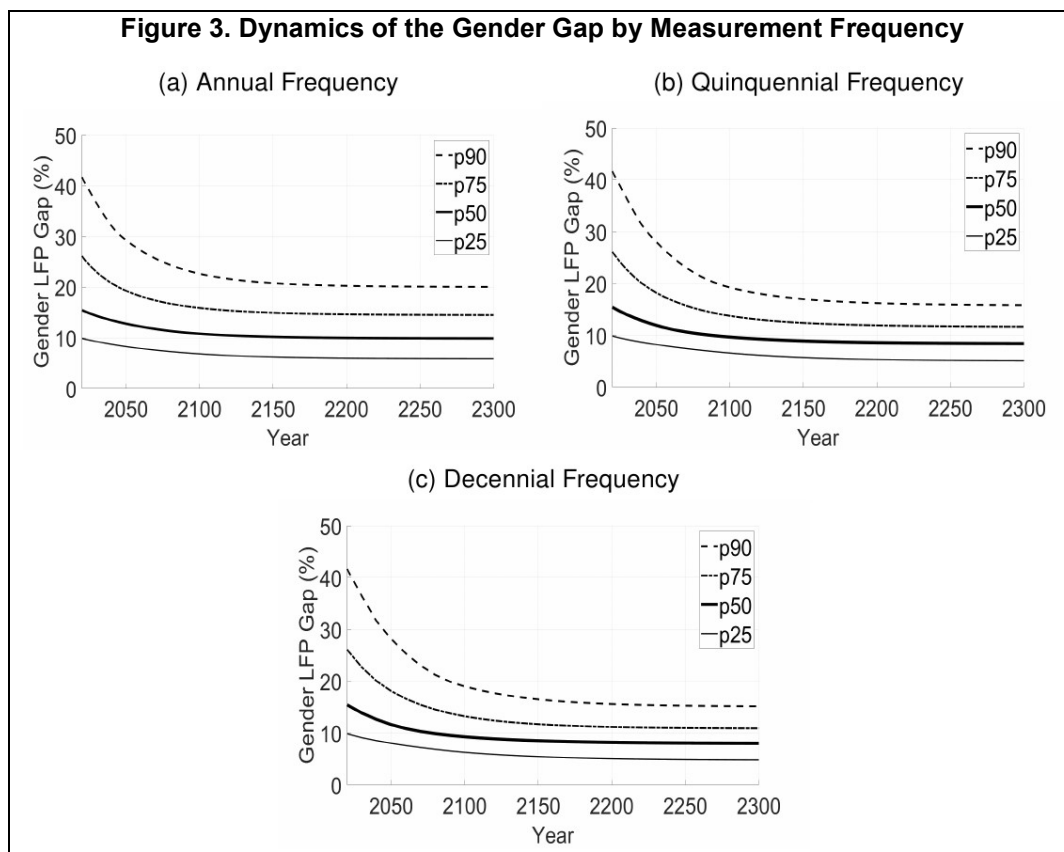
Table 2 displays the number of observations in each bin and the bin cutoffs for our complete sample. The table shows how a focus on multi-year transitions can decrease the number of observations substantially. We stop at a model with 10-year transitions as it balances dynamic stability of the data with precision of the estimates.

<u>Gap Category</u>	<u>Lag Order 1</u>	<u>Lag Order 5</u>	<u>Lag Order 10</u>
Under 3.37	281	241	198
3.37 to 6.62	287	248	195
6.62 to 11.56	835	662	470
11.56 to 18.33	1,413	1,220	966
18.33 to 30.06	1,424	1,255	1,030
30.06 to 46.39	858	767	663
46.39 to 53.93	285	257	223
Above 53.93	287	264	224
Total	5,670	4,914	3,969

*The gap category cutoffs are the 5th, 10th, 25th, 50th, 75th, 90th and 95th percentiles of the sample distribution.

Figure 3 below presents our results for the three models resulting from using the full sample under the three frequencies described in Table 1.

Our first observation is that, for the methods compared in Figure 3, the transitional period lasts until about the year 2150, and all percentiles decline gradually over time. This is good news. There will be notable narrowing of gender gaps over the next two centuries, if the policies, trends, and pattern of shocks of recent years continue to prevail in the future.



The bad news is that a substantial fraction of the distribution of countries will continue to exhibit sizable LFP gender gaps over time.

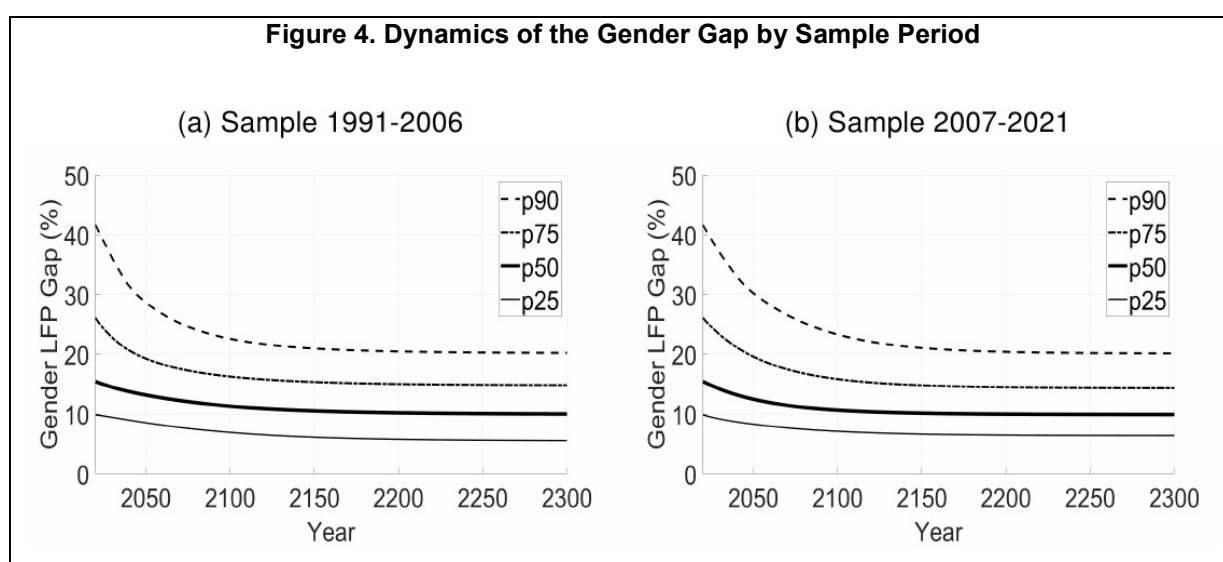
- First, *the 25th percentile exhibits the slowest convergence, delaying the closing of the gap even for countries with relatively small gaps.* In all panels, the 25th percentile is the last curve to fully flatten.
- Second, *the median (50th percentile) of the distribution converges to a value of approximately 10 percentage points in all exercises.* This result is roughly consistent with our introductory exercise, which resulted in 40 percent of the countries with gaps above 10 percentage points in the long run.
- Third, across all exercises, the 90th percentile of gaps is located above roughly 15 to 20 percentage points in the long run.

Figure 3 thus shows that our introductory result holds even at higher granularity and lower frequency of observation.

We now compare the results obtained using the first versus the second half of the data when estimating one-year transition probabilities. While one would expect the dynamics to have changed over time, giving

rise to a faster and narrower convergence, we observe that this conjecture is not strongly supported by data. The later sample in Figure 4 (b) in fact implies faster convergence mainly for the 25th percentile, which flattens by year 2100, while it flattens after year 2200 with the earlier sample used in Figure 4 (a). This means that *the closing of the gap at the bottom of the distribution has accelerated slightly over time. However, such faster convergence is accompanied by slightly higher gaps in the long run for the more recent sample*, as can be seen more clearly by comparing the last two rows of Table 3.

Table 3 contains a numerical summary of the long-run distributions implied by the Markovian models presented in Figure 3. It shows that, depending on the methodology, the top 10 percent of countries with highest gaps will have gaps above 14.6 to 20.7 percentage points in the long run.



Regarding speed of adjustment, Table 3 shows that the gaps will move within 1 percent of their long-run value after between 197 and 300 years and that they will move within 0.1 percent of their long-run value after 295 to 430 years.

Table 3. Long-Run Distribution and Years to Convergence by Method

Method	p25	p50	p75	p90	Years to Convergence	Years to Convergence
					(1%)*	(0.1%)**
Annual Frequency, Full Sample	6.4	10.2	14.8	20.2	203	304
Quinquennial Frequency, Full Sample	4.9	8.3	11.4	15.4	300	430
Decennial Frequency, Full Sample	4.7	8.0	10.8	14.6	300	430
Annual Frequency 1991-2006	5.4	10.1	15.1	20.7	269	392
Annual Frequency 2007-2021	7.1	10.2	14.3	19.5	197	295

*First year at which all percentiles are less than 1 percent away from their long run value.

**First year at which all percentiles reported are less than 0.1 percent away from their long run value.

In Table 4, we re-compute all our results excluding the years 2020 and 2021 from the sample to purge any potential effects of the Covid-19 pandemic. We find that, for the Annual Frequency, Full Sample case, all percentiles are pushed downward, with the 25th percentile cut most (by 0.6 percentage points) and

Method	p25	p50	p75	p90	Years to Convergence	Years to Convergence
					(1%)*	(0.1%)**
Annual Frequency, Full Sample	5.9	9.9	14.5	20.0	215	319
Quinquennial Frequency, Full Sample	5.0	8.4	11.6	15.7	280	405
Decennial Frequency, Full Sample	4.8	8.0	10.9	15.1	290	400
Annual Frequency 1991-2006	5.5	10.0	14.8	20.2	267	390
Annual Frequency 2007-2019	6.4	9.9	14.3	20.1	196	293

*First year at which all percentiles are less than 1 percent away from their long run value.
**First year at which all percentiles reported are less than 0.1 percent away from their long run value.

gradually less for higher percentiles (with a cut of by 0.2 percentage points at the 90th percentile). The percentiles generated by other methods are not impacted systematically, as shown in rows 2 to 5 of Table 4, while the time to convergence is roughly similar across the two samples with longer convergence time for the Annual Frequency, Full Sample case.

On one hand, the results (that the percentiles are lower without the Covid-19 years) highlight *the devastating effect of the pandemic on the status of women for countries with substantial progress*, which has been documented in the literature (see, for example, Fabrizio and others, 2021, and Alon and others, 2021). On the other hand, they reiterate the results obtained in Figure 4(a), that *the convergence of the 25th percentile takes longer when its value is lowest*. This points to the need for attention to closing gender gaps across the distribution and not just where gender gaps are the largest.

Also, as shown in Appendix III, our results are not caused by the potentially mismeasured non-representative dynamics of a few countries with presumably large measurement errors. In fact, we find that the long run distribution of the gap exhibits higher percentiles when large countries receive more weight in our estimations. This suggests certain countries with very large populations exhibit gap dynamics that elevate the long-run stationary distribution.

The following section complements the univariate analysis and links our paper to the literature on U-shaped transitions by considering the joint evolution of the LFP gender gaps and the wealth of nations. We do so by analyzing a bivariate Markov chain that describes the joint dynamics of these variables and, as before, projecting the future evolution of the joint distribution produced by such Markov chain, including the long-run stationary distribution.

IV. Accounting for Development

How much would accounting for the interplay of development and gender gaps impact our transition paths of the gender gap distribution? To answer this question, we extend our main methodology from a

univariate Markov chain describing the movement of the distribution of country-level gender gaps, to a bivariate Markov chain that jointly describes the movements of the joint distribution of income and LFP gender gaps across countries.

Although it is still the subject of debate, some authors have interpreted cross-country data (see, for example, Goldin 1995) as evidence of forces that, on average, would lead countries to have a nonmonotone (or “U-Shaped”) transition toward gender equality as a function of economic development.⁶ In a nutshell, the U-shaped view goes like this: (i) low-income countries would have a low gender gap in labor force participation out of bare necessity. (ii) As the countries’ incomes increase, families can “afford” having the women not work as much and, for several reasons (e.g., investing in children’s education), their participation in fact falls as the country reaches a middle-income level. (iii) Finally, as the country’s income approaches that of advanced economies, and the institutional framework provides the right conditions, female participation rises, the gender gap falls back down, and the country approaches gender equality.

In relation to this view, we first note that the methodology we employ allows challenging the implicit notion that the wealth of nations and gender equality follow deterministic paths that eventually achieve gender equality. Our baseline methodology allows for, but does not impose, convergence to a degenerate cross-country distribution of the gender gap.⁷ In this sense, we allow for the possibility that countries may be moving slowly but surely toward some level of gender equality in outcomes, although the data so far do not support this possibility.

As noted, the key reason for this result is the fact that some countries experience episodes of increasing gender gaps. These episodes could relate to shocks, policies, or, to a lesser extent, to backtracking or reversion of advances in gender-neutral laws, policies, and social norms. Table 5 shows how the cases of increasing gaps in our data are distributed across IMF region and country income categories.

Table 5. Observations with Increasing Gender Gap Category by IMF Region and Income Group (%)*

	Advanced Economy	Emerging Market	Low Income Country	Total
Africa	0.0	2.7	17.0	19.6
Asia-Pacific	1.8	2.7	9.8	14.3
Europe	16.1	8.9	2.7	27.7
Middle East and Central Asia	0.0	17.9	2.7	20.5
Western Hemisphere	0.0	17.9	0.0	17.9
Total	17.9	50.0	32.1	100

*Each observation counted in the table represents one annual observation for a country in which the gender gap moved up by one or more categories of our 8-category model, described in the previous section.

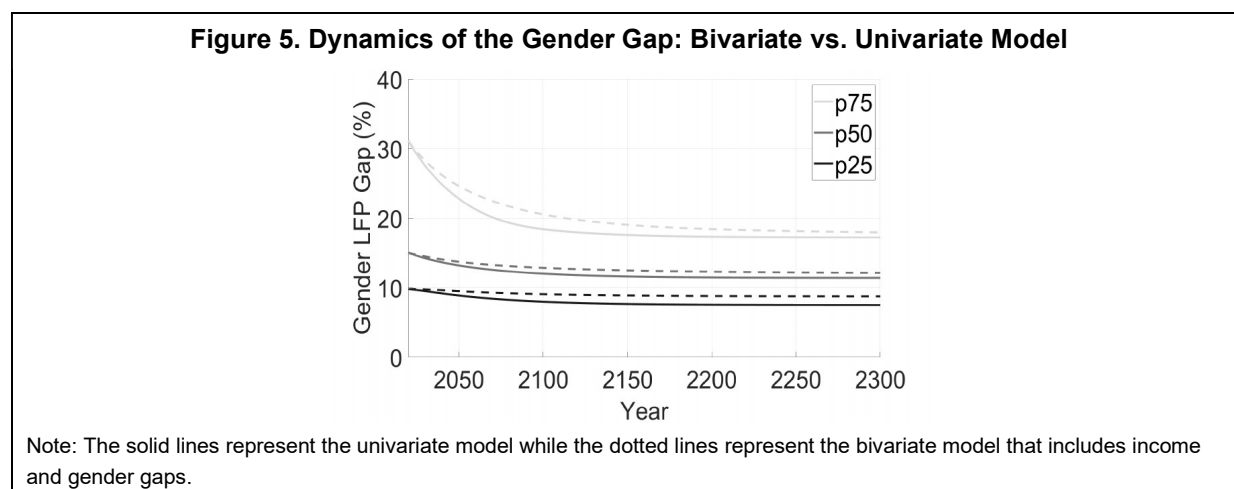
⁶ This view has also been studied in panel data and for a single country over time (see, for example, Ngai et al. 2022).

⁷ A probability distribution is said to be degenerate if it consists of a single value that occurs with probability 1. In our case, such distribution would assign the exact same value of the LFP gap to all countries.

The table clearly shows the existence of significant evidence of increasing gender gaps within all regions and income levels of the world.⁸

We now investigate the potential quantitative consequences of having abstracted from country income for our baseline results. The direction and magnitude of the effect are hard to foresee. On one hand, mixing high-income country data in the dynamics of low-income countries may have biased our long-run gaps downward in our previous section, by diluting the upward probabilities. On the other hand, having abstracted from the fact that countries may be either moving toward the mean world income (as in Barro and Sala-i-Martin, 1992) or away from the mean world income (as in Quah, 1993) could also bias the probabilities. The direction of the bias depends on the direction of the convergence, on the skewness of the initial distribution, and on how the dynamics of the gender gap may vary above and below the mean of income. Clearly, if countries were marching along a U-shaped transition, we would observe very low probabilities of an upward transition for high income countries. Therefore, conditioning the probabilities by income could result in lower percentiles in the long run, when more countries reach high incomes.

We measure country income as the ratio of real GDP per capita to the global sample average of the same variable in each year. We then make some adjustments to our baseline methodology to ensure an appropriate number of observations in each category. We set the cutoffs for our categories to the 10th, 25th and 75th percentiles of the LFP gender gap, and, for the income variable, we set the cutoffs to the 25th and the 75th percentiles. This yields a total of 12 categories for the Markov chain. In Figure 5, we compare univariate and bi-variate results keeping all other aspects of the methodology constant. Figure 5 shows the transition paths for several quantiles for each of the 2 versions of the exercise while Table 6 displays the comparison of the quantiles of the ergodic distribution.



⁸ Narrowly speaking, this result allows us to conclude that our non-degenerate long-run distribution does not come exclusively from countries that could be presumably moving “out of poverty” along the increasing section of the well-known “U-Shape” transition idea. In other words, even if countries were deterministically marching toward economic prosperity, our main qualitative conclusion about gender gaps would remain valid: the data do not suggest convergence to a single gender equality point, common to all countries but rather convergence to a long run distribution with positive gaps for most countries.

In general, we find that the transitional dynamics are similar in the bivariate and univariate cases. All the percentiles drop monotonically toward their steady state values.

Method	p25	p50	p75	Years to Convergence (1%)*	Years to Convergence (0.1%)**
Bivariate	9.9	14.5	20.0	215	319
Univariate	8.4	11.6	15.7	280	405

*First year at which all percentiles are less than 1 percent away from their long run value.
**First year at which all percentiles reported are less than 0.1 percent away from their long run value.

The long run distribution in the bivariate case converges to a vicinity of 1 percent of its long run value in 25 years, faster than the univariate case, which takes 280 years under this specification. The mixing of high-income countries, which have lower probabilities of upward movements in LFP gender gaps than low-income countries push the probabilities of such transitions in a downward manner in the univariate case. Regardless of what is viewed as the “right” model, the robustness of our main result holds.

V. Conclusions

We have presented a simple exercise to understand the dynamics of LFP gender gaps implied by the international experience between 1991 and 2021. During some time periods, some countries have increasing gaps over time. If this remains the case, the global gap will not “close”. Instead, gender gaps will narrow but remain quite large for the foreseeable future, absent a significant step up in policies and measures to prioritize closing the gaps.

Our analysis also suggests that the dynamics of narrowing the gender LFP gaps are very slow, with stationarity (within 1 percent of the long-run steady state) requiring 197 to 430 years. Clearly, stronger policy interventions are needed to prioritize and achieve women’s economic empowerment that benefits not just women but societies. The logic of Markov chains teaches us that the interventions should be focused not only on reducing gender gaps but also in maintaining low gaps in countries where more progress has been achieved, as this is the only path to a uniform global closing of the LFP gender gap—or, in other words, sustained utilization and improved allocation of human resources. The analysis also shows that attention should be paid not only to countries where the gaps are the largest, but also across the distribution including where gaps are narrower and where further progress is also likely to be slowest (based on recent trends, policies, and patterns of shocks).

Our results are not exclusively caused by increasing gaps in emerging market and developing economies. In the data, the cases of increasing gaps are quite evenly distributed across IMF region and country income categories. Furthermore, when we analyze the joint dynamics of income and gender gaps, we find that taking development into account leads to slightly larger gaps in the long-run distributions. These results taken together caution about a deterministic transition toward gender equality along the development path. While the Markov chains potentially allow for these patterns, the data, however, do not provide support or evidence in its favor.

Looking ahead, the methods in this paper could be applied to the dynamics for other gender-relevant indicators and gaps. The robustness of the results to other methods (such as continuous-state methods) could be further examined. The link between the transition probabilities to explanatory factors, institutions, and policies are also among the list of interesting extensions that could be explored in future work.

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Appendix 1. Deterministic Trend Methods for Time-to-Gender-Equality Calculations

In this appendix, we further explain the determinist-trend methods. To do so, we first calculate time trends in two ways. In the first way, we take the logarithm of the gender gap for each country and then regress that variable against the year variable, which is simply the year in which the gap was measured. In the second way, we regress the raw gender gap (instead of its logarithm) against the year variable.⁹

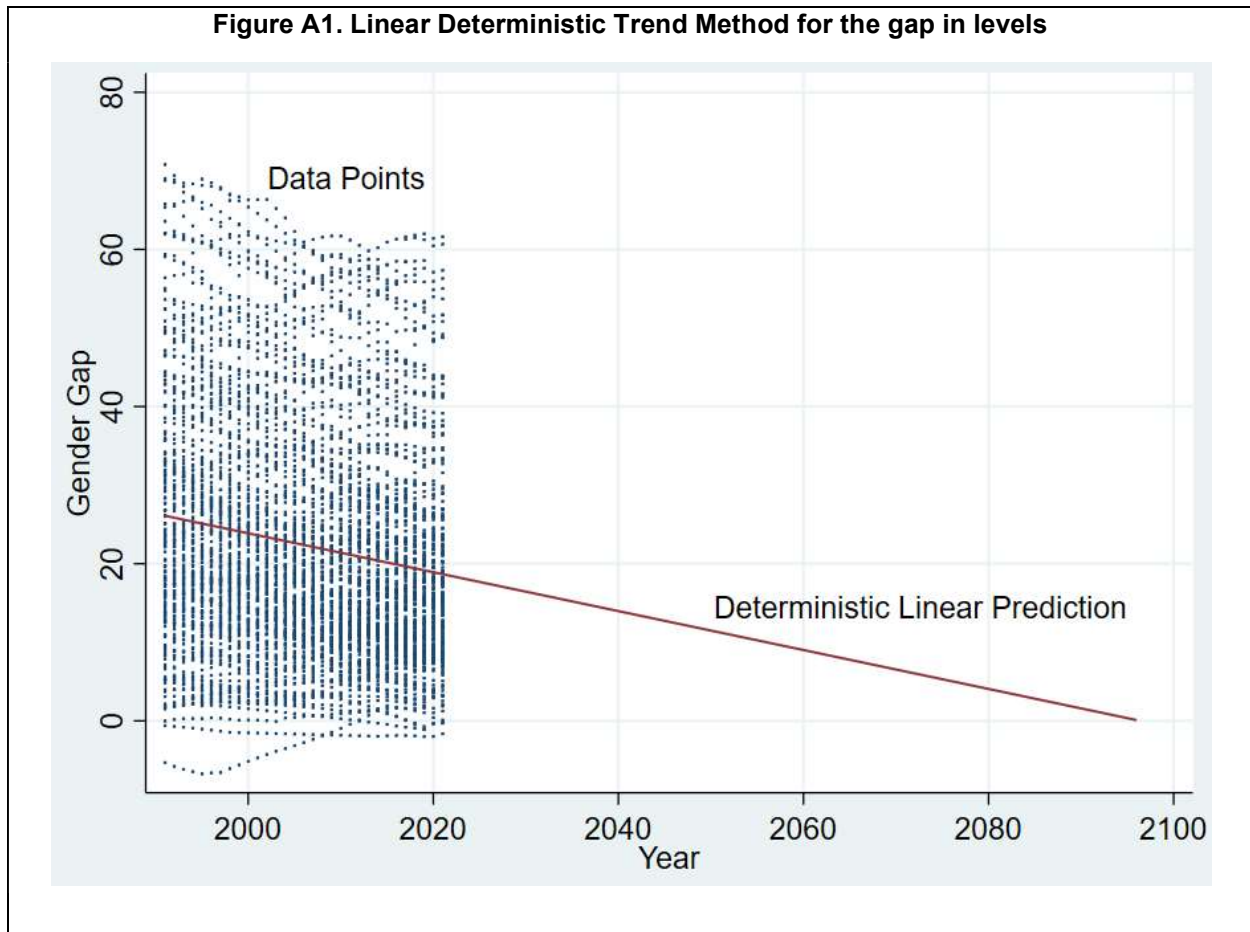
The regression coefficient for the time trend on the log of the gender gap is 0.0107 (which means that the gap falls by approximately 1.07 percent per year). The coefficient we obtain for the gap in levels is -0.24 (this means that the gap falls by 0.24 percentage points every year).

Using each of the time trends, we can then extrapolate the average gender gap until its level reaches zero. Starting from the average gender labor force participation gap of 19.49 percent observed in year 2020, a trend based on the logarithm reaches zero in 425 years while the trend based on the levels of the gap reaches zero in $19.49/0.24=81.21$ years.¹⁰

Figure A1 describes the last method graphically. The panel data are represented by the cloud of points, while the best fitting linear trend, extrapolated until it intersects the horizontal axis, is presented as a brown line.

⁹ We thank Diego Gomes for suggesting this method. Also, through private communications the authors have established that a similar linear method based on the annual levels of a global gender equality index is used by the World Economic Forum “Gender Gap Report” to produce their annual estimate of the remaining time to gender equality.

¹⁰ In the logarithmic case, the number of years t solves the inequality $0.01 = (1 - 0.0107)^t$.



The R-squared statistics of the regressions giving rise to each of these models are 0.0214 and 0.0134, respectively, reflecting vast heterogeneity in the gender gaps across countries, but are, in essence, not too different. The fit to the data is rather poor, as measured by the R-squared statistic.

Appendix 2. Interpolation Method for Quantiles of Gender Gap Distribution

Our method consists of interpolating the approximate cumulative distribution function (CDF) of the gender gap produced by our Markov chain model by applying a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) available from `interp1` in Matlab.

In particular, prior to estimating the transition matrices, we fix the cutoffs for our Markov states in a vector $x=\{x_0,x_1,x_2,\dots,x_N\}$. We set points 1 to $N-1$ to match certain percentiles of the gender gaps in our dataset, while we set point x_0 and x_N to the minimum and the maximum in our dataset.

Using this vector, we calculate the CDF of countries across categories in 2020 as $\{0,F_1,F_2,\dots,F_N\}$, where $F_N=1$ and the items of the PDF are given by $F(n)-F(n-1)$. We can use the transition matrix to simulate the future path of the PDF and reconstruct the CDF for each simulation year.

For any given percentile of the distribution p in $[0,1]$, we locate the value of the point p in the grid given by $\{0,F_1,F_2,\dots,F_N\}$ and use the interpolation technique to find the value x from the image given by array $\{x_0,x_1,x_2,\dots,x_N\}$.

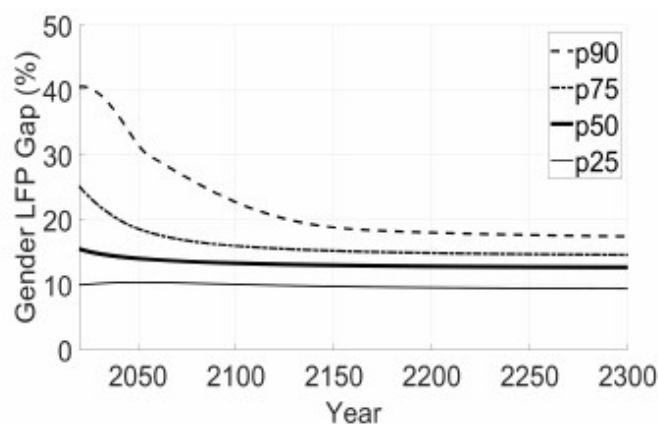
Appendix 3. Mitigating Measurement Error

The empirical literature often addresses the impact of measurement error by using alternative measures like those produced by validation studies of surveys. In the case of male and female labor force participation, we use the ILO dataset because it is the only harmonized and balanced panel for these variables available to the best of our knowledge. To attempt to gauge the potential effect of measurement error, while maintaining the country as the unit of observation, we assume that measurement error is decreasing in population size. That is, we assume that countries with larger populations have more stable and accurate statistics. In this vein, we recompute the annual frequency full-sample transition matrix using population weights that increase the importance of each observation in proportion to the country population.¹¹ The results of this exercise are depicted in Figure 6.

While our motivation to weigh the country level gap observation using population is to address potential measurement errors in smaller economies, alternative interpretations to the results of this Appendix could be considered. For example, this could show that our results are robust to population weighting, or if changing the unit of observation from countries to individuals may affect the result.

It is clear from the path for the selected percentiles in Figure 6 that certain countries with very large populations have dynamics that tend to increase the long-run gaps, and conversely that smaller countries have dynamics that tend to decrease the gaps. In this sense, our main results are robust and, under the assumption that measurement error decreases with population size, measurement error tends to bias the percentiles downward, so our result can be interpreted, under these assumptions, as a lower bound for the long run gaps.

Figure 6. Dynamics of the Gender Gap: Population Weights



*The weight assigned to a country-year observation consists of the ratio of the country's population to the world population in that given year. The weight is applied with the option "aweight" in the tabulate Stata command this assumes that the implicit variance of the (measurement error of the) observation is inversely proportional to the country's population

¹¹ We thank Jiajia Gu for suggesting this robustness check.



PUBLICATIONS

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