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A double-edged sword: technology, prosperity and inequality

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Abstract

Digital technologies promise myriad dividends for development while evidently widening divides across gender and space. This contrast deserves critical scrutiny based on national samples to prevent either complacency or despondency. We began with a theory of technology-driven wage inequality in developing countries. Then two hypotheses were tested: (1) smartphone use (to seek information on the web) increases probability of securing formal sector jobs which are more productive, thus increasing prosperity; and (2) across the formal sector, such use delivers larger gains at higher quantiles, thus deepening wage inequality. To test the first hypothesis, a discrete factor estimator was applied, since both treatment and outcome are binary indicators; and since the wage gains are uneven, instrumental variable quantile estimator was used to test the second. Using a national socioeconomic survey in 2014 matched with a separate village census in the same year, we studied 82,283 working age Indonesians (15 to 55 years), their jobs and wages. This revealed transformations in the labour market driven by mobile technology: smartphone use narrowed the gender gap in formal employment by five percentage points. In contrast, wage inequality was widened with a thicker wedge driven by men's higher wage. The complex effects of digital technologies on labour market outcomes demand a strengthening of analogue bases of digital technologies, for example gender parity in educational attainment and in internet access to ensure the digital dividends are widely shared. We close by discussing implications for global development, harnessing technology in responding to widening global inequality.

Keywords

smartphone, formal job, wages, inequality, skill, technological change, discrete factor model, instrumental variable quantile estimator

JEL Codes

J31, O33

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1. Digital dividends and digital divides

Digital technologies are ubiquitous and digital dividends are promised everywhere. Up to one-fifth of global economic growth has been claimed by investment in digital technologies in the past two decades (World Bank 2016). New firms become exporters, riding on digital infrastructure criss-crossing the globe in wired and wireless forms (ibid, 59ff). These benefits are not limited to countries and firms alone, as individuals have also gained. In the UK, people aged 50 and over are benefiting from online social connections in helping to maintain their cognitive function over an extended period in later life (Tampubolon 2015).

Meanwhile, evidence from developing countries is accumulating, echoing this encouraging note. Jensen (2007), in a widely cited study, showed that the introduction of mobile phones led to a dramatic narrowing of price dispersion and waste reduction in coastal fish markets in South India. Both consumers and producers reaped digital dividends. Across the globe in Peru, South America, workers and households gained in welfare from digital technologies (De los Rios 2010). In a short panel study, 2007-2009 internet use by Peruvian workers led to an increase in wages, though for informal or self-employed workers the evidence is rather weak. Moreover, the author also found no effect of internet use on the probability of securing a formal job.

But recent evidence from Indonesia has offered a caution. Access to internet in Indonesia remains unequal and in fact this inequality is intensified along persistent social cleavages, such as gender and centre-periphery disparity (Sujarwoto and Tampubolon 2016). Far from moving towards convergence in the period 2010-2012, the internet divide expanded; the inequality of internet access by age, gender, income, and education widened across urban-rural, city-countryside, and remote island-mainland island areas. The analyses indicated that supply side variation across districts—particularly in telecommunications infrastructures, human capital and education services—is associated with the internet divide. The World Bank report (2016), Digital Dividends, also chimed with this discouraging note. Despite the offer of online citizen feedback in Indonesia (LAPOR), few took up the opportunity to demand better public service, preferring instead to free-ride on others', as also observed in the Philippines and Botswana (ibid, 166-167).

Because of this combination of potential dividend and mixed evidence, more investigation is needed, especially on labour market benefits among the working age population. Digital technologies such as smartphones (with internet access) can be instrumental in securing jobs in the more productive sector of the labour market in developing countries, namely, formal jobs (World Bank 2016). By reducing information asymmetry between employers and job seekers, digital technologies can help a job seeker secure a formal job. The formal sector is widely known to be a more rewarding and productive part of the economy of developing countries; see for instance Breman (2013) on India and Basri (2009) on Indonesia. In Indonesia, for instance, the median pay for informal workers is less than $1 an hour, and informal enterprises are extremely unproductive compared to formal firms with the median informal enterprise having a value added per worker of less than 5% of that of an average formal firm (Rothenberg et al 2016). No less importantly, formal sector jobs also contribute more to public finance. The authors noted that informal enterprises in Indonesia tend to avoid paying taxes, depriving government of resources to invest in and maintain public infrastructure. Thus by increasing probability of securing formal sector jobs, digital technologies enable workers to be more productive and government to administer tax more efficiently, improving individual and government outcomes which enhance prosperity.

The myriad digital dividends coinciding with the widening digital divide outlined above points to a complex working out of the roles of digital technologies in development. Another layer of complexity arises out of the skill requirement in the adoption and efficient use of the technologies in the labour market as encapsulated in the thesis of skill biased technical change. There is a vast literature on the increasing skill bias in returns to factors of production (labour and capital). Over the last four decades the share of labour in national income has been declining as more capital (increasingly capable machinery) is used by disproportionately fewer workers. Concurrently two changes are taking place: highly skilled workers command even higher wages while at the same time middle skill occupations are being automated away, which together creates a hollow in the middle of wage distribution (Van Reenen 2011). This is an experience that developed countries are currently going through. In developing countries the possibility that digital technologies drive some workers to earn disproportionately more while failing to create middle income jobs, thus deepening wage inequality, though plausible is yet to receive critical examination. To focus our investigation two hypotheses are tested.

- Formal job hypothesis: smartphone use by job seekers increases the probability of securing formal sector jobs.
- Wage inequality hypothesis: across the formal sector smartphone use increases wages with disproportionate increases in the higher quintiles.

This study makes three contributions. It presents evidence on the effect of smartphone use on securing more productive jobs in a developing country. It also presents new evidence on technology driven wage inequality. Its last contribution arises from the unique juxtaposition of the prosperity and inequality effects of digital technologies in one empirical study by discussing their implication for global inequality.

Our contributions speak to a few streams of literature. By providing a complex and nuanced evidence on the effects of digital technologies in Indonesia, it speaks to the emerging literature on digital dividend and digital divide as recently summarised in the World Development Report. By drawing inspiration from the skill biased technical change literature, the study speaks to this literature from the experience of developing countries. Also, to the literature on technological innovation it attests the complex changes brought about by general purpose technologies such as, steam power, electricity, digital technologies, biotechnology and nanotechnology.

2. Theory

We simply note that the formal job hypothesis builds on the role of digital technologies in reducing information asymmetry between employers and job seekers (World Bank 2016). Digital technologies such as smartphones enable convenient and timely access to job vacancies. But for the wage inequality hypothesis, a skill biased technical change in the context of developing countries needs a formal exposition; see an earlier theoretical model in Chennells and Van Reenen (2002) and a reduced form model in Vivarelli (2004). Following van Reenen (2011) the constant elasticity of substitution production function reads:

$$Y = \left[\lambda n_h^{\frac{\sigma-1}{\sigma}} + (1-\lambda) n_l^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where Y is value added, λ is multiplier of skilled workers' contribution giving $\frac{\lambda}{1-\lambda}$ as technology bias, the subscripts indicate high and low skills such that n_h is supply of high skilled workers, and σ is elasticity of substitution between the two skill groups ($\sigma = 1$ in Cobb-Douglas production function). Assume that product and input markets are perfectly competitive so the two first order conditions are combined to give relative wages as:

$$\ln\left(\frac{w_h}{w_l}\right) = \ln\left(\frac{\lambda}{1-\lambda}\right) - \frac{1}{\sigma}\ln\left(\frac{n_h}{n_l}\right). \tag{2}$$

Under the standard Tinbergen assumption that technology bias is a long run trend, an equation for estimating the evolution of inequality is:

$$\ln\left(\frac{w_h}{w_l}\right) = \gamma t - \frac{1}{\sigma}\ln\left(\frac{n_h}{n_l}\right) + \varepsilon. \tag{3}$$

The evolution of wage inequality depends on the trend of technology and the growth of supply of high relative to low skilled workers. Estimating (3) using a quarter century of time series data from the US gave σ = 1.4 and γ = 0.03 or about 3% annual growth (Katz and Murphy 1992).

What does a suitable theory for developing countries look like? To understand wage inequality due to technology in developing countries in the short term we also begin with (2). On the right hand side: because in these countries the introduction of technology from the global frontier (Howitt 2005, Aghion and Howitt 2009) is much quicker than the training of highly skilled workers through graduate school, the growth of supply in the short term is highly inelastic and can be assumed constant hence subsumed in the error term for estimation purposes, ie $\left(\frac{1}{\sigma}\right)\ln\left(\frac{n_h}{n_w}\right)$ ~ constant. Witness the quick succession of Samsung phones or iPad tablets in the hands of college students in Jakarta, Delhi, or Lagos. On the left hand side: for the same inelasticity reason, the technology bids up the price of high skills before working its way down, so ratio can be replaced with level, ie $\ln\left(\frac{w_h}{w_l}\right) \sim \ln w$.

3. Estimation

Thus for developing countries the skill biased technological change gives an equation for estimation

$$\ln w \ = \gamma t + \beta X + \epsilon \qquad (4)$$

where w is wage, t is technology (smartphone use), X is a vector of other factors in a wage equation. Comparing (2) and (4) suggests first, $\mathbb{E}(t\epsilon) \neq 0$ ie smartphone use is endogenous, hence we need exogenous variations or instruments driving smartphone use; and second, the effects of smartphone use are different along the distribution of wages, with higher effects expected in the higher quintiles. This means, for instance, because the outcome is log wages, $\gamma_{50}$is the effect *above*, not at, the median wage so the wage inequality hypothesis posits among others that $\gamma_{50} > \gamma_{10}$. To test the wage inequality hypothesis, instrumental variable quantile estimator was applied (Powell 2016) as implemented in Stata.

Separately, to test the formal job hypothesis we note that both the treatment (smartphone use) and the outcome (securing a formal job) are binary indicators. Treatment may be endogenous due to an unobserved factor affecting both the treatment and outcome. Often linear instrumental variable estimator or two-stage least squares estimator was used, ignoring the binary scale of the outcome. An alternative estimator is joint parametric estimator, assuming bivariate normal distribution of the outcome and treatment errors. The unobserved factor is assumed to be normally distributed. The joint model of formal job j and smartphone use t becomes

$$j^* = \beta_1 t + \beta_2 X_1 + \epsilon_1 \qquad (5a)$$

$$t^* = \alpha X_2 + \epsilon_2 \qquad (5b)$$

where $j^*$and $t^*$are the latent propensities of formal job attainment and smartphone use; we observe $j = 1$ if $j^* \geq 0$,

similarly $t = 1$ if $t^* \geq 0$, $\mathbb{E}(\epsilon_1) = 0$, $\mathbb{E}(\epsilon_2) = 0$, $\operatorname{var}(\epsilon_1, \epsilon_2) = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1 \\ \rho\sigma_1 & 1 \end{bmatrix}$.

As written, one of the variances is set to 1 for identification; in Stata both variances are in fact set to 1. With this parametric assumption, the set of variables in $X_1$and X_2 can completely overlap, with no need for extra exogeneous variations (instruments) in X_2.

Here we relaxed the assumption that the errors were parametrically distributed following recent developments of discrete factor joint model for non-linear outcome (Guilkey and Lance 2014), building on Mroz (1999) and Heckman and Singer (1984). Instead, the errors are distributed non-parametrically, letting the data determine the many discrete modes and mass of the errors. Both Singer and Heckman (1984) and

Mroz (1999) found two modes estimated from the data were sufficient. Therefore our preferred joint model of j and smartphone use t is

$$j^* = \beta_1 t + \beta_2 X_1 + \delta\eta + \epsilon_1 \tag{6a}$$

$$t^* = \alpha X_2 + \eta + \epsilon_2 \tag{6b}$$

where $\mathbb{E}(\epsilon_1) = 0$, $\mathbb{E}(\epsilon_2) = 0$, and η is non-parametrically distributed (discrete factor) with its coefficient set to 1 in one of the equations for identification. The average treatment effect of smartphone use on the probability of securing formal job is $\mathbb{E}(j|t = 1) - \mathbb{E}(j|t = 0)$. To ascertain whether the analysis was robust we compared the results of discrete factor model and those of bivariate normal model.

Although exogenous variations or instruments are not strictly necessary to estimate the effect of smartphone use on formal job acquisition, to help the numerical algorithm we used additional information in X_2 obtained from a separate village census: the presence of a base transceiver station and wireless signal strength in each of the 82000 villages in Indonesia.

It is assumed that the exogenous variation in these instruments of base transceiver location and wireless signal strength are correlated with decisions by local people to use mobile phone to browse the web. Conditional on other covariates, the instruments will be correlated with the use of a mobile phone for browsing the web (the relevance condition). Another condition on the instruments is the exclusion restriction, which is known to be untestable (Heckman 2001). What would be the reason for the instruments' exclusion and how could it fail, thus threatening inference? We maintain that being in an area where a base transceiver station is located or where the wireless signal is strong is only correlated with the decision to use smartphones to browse the web, but with no direct effects from the location and signal on formal job acquisition or wages apart from those working through smartphone use. This reasoning can fail in the following instance: as commercial entities, network operators may build base transceiver stations in areas that have higher average expenditure or more purchasing power per person. In such areas it is also likely that more people use smartphones, are found in the formal sector and earn higher wages; correlations between them are therefore due to higher average expenditure. Unless this is accounted for, inference will be biased upward. We mitigate this threat by including average income per person in each province. Thus, conditional on all the covariates, the instruments are taken to be exogenous.

4. Materials

The Indonesia socio-economic survey (*Susenas*) 2014 collected information on labour market outcomes as well as social and demographic characteristics of a nationally representative sample. This survey was matched based on a district identifier with a village census (*Potensi Desa*) of 82,000 villages in the same year, augmenting the survey with the average number of base transceiver stations and wireless signal strength in all 514 districts. In addition, information on income per person in all

Indonesian provinces was obtained from the Ministry of Finance. The focus of estimation is the working age population (15–55 years). Because of the gender and geographic digital divides (Sujarwoto & Tampubolon 2016) the sample was analysed separately; for the same reason, only urban residents were studied.

Formal job status was defined by the National Statistical Agency (*Badan Pusat Statistik*); see also World Bank (2010). Monthly wage information was elicited using the question: “How much do you receive from your main occupation monthly?” The treatment, smartphone use to access the internet, was derived from two questions on whether the respondents had used mobile phones and had accessed the internet in the last three months: “Did you use a cell phone in the last three months? Did you use it to access the internet in the last three months?” Household and personal characteristics are known to influence many economic decisions in developing countries like Indonesia, therefore, the following information was also included: expenditure per person to reflect household’s economic position, household head’s education, marital status (married or not), and the person’s years of schooling.

5. Results

Key covariates in Table 1 characterise the analytic sample: more women (50.5%) than men (49.5%); and predominantly working in the informal sector (61.7%); with 29.1% of the sample having used smartphones to seek information on the internet.

Table 1: Key characteristics of the analytic sample

	N	Mean, %	Std. Dev.	Min.	Max.
Age	82,283	33.6	11.7	15	55
Women	41,549	50.5%			
Men	40,734	49.5%			
Wages	50,299	2.4M	29M	50000	96M
Log wages	50,299	14.333	.929	10.820	18.380
Formal	31,492	38.3%			
Informal	50,791	61.7%			
Smartphone user	23,976	29.1%			
Not smartphone user	58,307	70.9%			
Family head’s education	82,283	8.5	3.6	0	16
Married	50,348	61.2%			
Non-married	31,935	38.8%			
Years of schooling	82,283	8.8	3.8	0	16
Log exp per person	82,283	14.121	.897	10.703	19.173
Average province income	82,283	7.7e+14	6.2e+14	3.1e+13	1.7e+15
Base transceiver station	82,283	.743	.1629289	.255	1
Wireless signal strength	82,283	1.955	.0712896	1.621	2

The results of modelling whether smartphone use helped secure a job in the formal sector, separately for women and men, are summarised in Table 2. The discrete factor models for both working age women and men showed that smartphone use was statistically significant in raising the propensity to secure a formal job, which accords with the formal job hypothesis.

The average treatment effect of smartphone use for women is

$$\mathbb{E}(\text{formal job} \mid \text{mobile web user}) - \mathbb{E}(\text{formal job} \mid \text{not mobile web user}) =$$
$$0.536 - 0.244 = 0.292$$

whereas for men it is

$$0.707 - 0.468 = 0.239$$

On average, men have a higher probability of securing formal jobs, but improvement due to smartphone use is higher among women: 0.292 versus 0.239. These differential effects of technology have rarely been noted: technology narrows gender divide, by five percentage points in this instance.

Table 2: Working age female and male discrete factor model of formal job and smartphone use in Indonesia 2014 (N=82,283).

Job	Female			Male		
	coef	*z*	*p*	coef	*z*	*p*
Constant	-1.975	-8.694	<0.001	0.209	0.934	0.35
Smartphone	4.792	29.950	<0.001	5.152	32.831	<0.001
Head's education	-0.004	-1.305	0.19	-0.014	-4.333	<0.001
Age	0.065	31.737	<0.001	0.061	29.041	<0.001
Married	-0.574	-16.869	<0.001	0.441	13.431	<0.001
Years of schooling	0.006	2.023	0.043	0.029	10.062	<0.001
Log exp per person	-0.131	-8.512	<0.001	-0.324	-21.357	<0.001
Province avg income	0.000	8.389	<0.001	0.000	5.693	<0.001
η	-2.929	-35.118	<0.001	-2.907	-36.507	<0.001
Smartphone						
Constant	-11.994	-41.602	<0.001	-12.405	-39.309	<0.001
Head's education	0.011	4.547	<0.001	0.020	6.452	<0.001
Age	-0.056	-59.651	<0.001	-0.056	-47.943	<0.001
Married	-0.443	-22.197	<0.001	0.040	1.438	0.15
Years of schooling	-0.007	-2.918	0.0035	0.002	0.797	0.43
Log exp per person	0.732	67.581	<0.001	0.818	64.262	<0.001
Province avg income	0.000	0.450	0.65	0.000	3.026	0.0025
Base transceiver station	-0.015	-0.269	0.79	0.334	5.370	<0.001
Wireless signal strength	1.108	8.441	<0.001	0.637	4.529	<0.001

Table 3: Female, instrumental variable quantile estimation of wages and smartphone use (N= 41,549).

Log wages	γ_{10}/SE	*p*	γ_{50}/SE	*p*	γ_{90}/SE	*p*
Smartphone	.544	<0.001	.349	<0.001	.186	<0.001
	.006		.009		.004	
Head's education	.013	<0.001	.008	<0.001	-.001	0.009
	.0004		.001		.001	
Age	.009	<0.001	.012	<0.001	.0145	<0.001
	.001		.001		.001	
Married	.131	<0.001	.110	<0.001	.073	<0.001
	.006		.007		.004	
Years of schooling	.028	<0.001	.011	<0.001	-.003	<0.001
	.001		.001		.001	
Log exp per person	.286	<0.001	.419	<0.001	.389	<0.001
	.003		.005		.002	
Province avg income	4.6e-17	<0.001	9.1e-20	0.983	2.5e-18	0.020
	2.4e-18		4.3e-18		1.1e-18	
Constant	8.400	<0.001	7.625	<0.001	8.882	<0.001
	.059		.074		.023	

Note: SE – standard error.

The effects of smartphone use on wages across the log wages of women workers in the formal sector are given on the first row of Table 3, where all effects are found statistically significant and positive. Higher wages were earned by smartphone users. These magnitudes are considerable, especially compared to the magnitudes among men below. Importantly, among women there is a monotone decrease in these effects along the log wage distribution. At the low end, compared to the non-users of smartphones, the users earned 54.4% higher wages, while around the middle, users earned only 34.9% higher wages (than non-users at comparable position in the distribution). Because of the monotone decrease in these positive effects, mobile technology does *not* increase wage inequality among women. There is no support for the skill biased technological change hypothesis among women.

Table 4: Male, instrumental variable quantile estimation of wages and smartphone use (N= 40,734).

Log wage	γ_{10}/SE	p	γ_{50}/SE	p	γ_{90}/SE	p
Smartphone	.181	<0.001	.203	<0.001	.168	<0.001
	.002		.003		.001	
Head's education	.002	<0.001	.002	<0.001	.001	<0.001
	.001		.001		.000	
Age	.007	<0.001	.010	<0.001	.011	<0.001
	.001		.001		.000	
Married	.424	<0.001	.301	<0.001	.288	<0.001
	.005		.002		.001	
Years of schooling	.020	<0.001	.003	<0.001	-.004	<0.001
	.001		.001		.000	
Log exp per person	.343	<0.001	.396	<0.001	.429	<0.001
	.001		.002		.000	
Province avg income	-1.7e-17	<0.001	-4.5e-17	<0.001	-1.9e-17	<0.001
	2.2e-18		9.4e-19		4.4e-19	
Constant	8.310	<0.001	8.351	<0.001	8.469	<0.001
	.0131		.022		.003	

Note: SE – standard error.

Similarly the effect of smartphone use on men's wages is significant and positive along the log wage distribution, as shown in the first row of Table 4. At the lower end, compared to non-users, smartphone users earned 18.1% higher wages; at the median of *log* wage distribution (this is equivalent to the 99 percentile in the wage distribution) smartphone use raised wages by 20.3%. Therefore, among men mobile technology *does* increase wage inequality, which accords with the skill biased technological change hypothesis.

On the wage inequality hypothesis, the data conveyed the same complex message of technology enhancing parity among women and widening inequality among men. Because men's wages have been higher than women's and men also make up the larger section of the formal sector, the result is a likely increase in wage inequality. Nevertheless, the fact remains that smartphone use narrowed the gender gap in the formal sector and reduced inequality considerably in women's wage distribution.

6. Discussion

The transformations brought about by digital technologies are being felt across developing countries. In Indonesia smartphone use is found to increase the probability of securing employment in the more productive formal sector and enhancing gender parity in formal sector employment. The digital dividends arising from this effect are at least two-fold. Workers in the formal sector, due to their skills and the capital goods at their command, can be more productive in delivering goods and services, thus enhancing consumer welfare. In addition, formal sector workers (Rothenberg et al 2016) contribute more efficiently to public finance (compared to the informal sector workers) through taxes and pension contributions, known as Askes Jamsostek, thus enhancing the resources available for government to govern.

Beyond raising welfare through enhancing parity, however, the analysis uncovered centrifugal digital forces likely to deepen inequality. Along men's wage distribution up to the 99th percentile, smartphone use increases wages at an increasing magnitude. In recent years inequality has been increasing in Indonesia, which now stands as the most unequal country among the founders of the Association of South East Asian Nations; Leigh and van der Eng (2009) noted for instance that the richest forty Indonesians have a share of wealth that is larger than the richest forty Americans of their country's wealth. Lower down the rank of the richest forty, technology may supply one explanation for why inequality has widened.

This wage inequality effect of digital technologies poses questions for development. What options are there, for public policy especially, to mitigate this? The viable option is to equip people in this race between people and technology by broadening the base for higher education and raising its quality. In Indonesia enrolment rates in higher education have been slowing down over the last two decades and remains highly unequal, with families at the bottom fifth of income distribution sending only 20% of their offspring to college. This is worsened with the low quality of education delivered in classrooms over the same period. The latest evidence from Trends in Mathematics and Science Study put 90% of Indonesian youths in the bottom 5% of the world distribution of mathematics and science scores. Education in Indonesia is therefore urgently in need of improvement to respond to this not-entirely-benign dynamic of digital technologies. Other developing countries with comparable education disparity and quality predicament should similarly consider this option.

The second challenge stands on the evidence of the digital divide in Indonesia (Sujarwoto & Tampubolon 2016). Because the digital divide overlaps with existing social inequalities, in particular gender inequality and centre-periphery disparity, the new evidence on the complex effects of digital technologies on labour market outcomes makes it even more urgent to bridge the divide. The authors showed that lack of infrastructure, especially electricity, is associated with lower rates of access to digital technologies. Now that digital technology is found to enhance the ability to secure more productive jobs, efforts to widen access to the technology should be supported, in particular through education and infrastructure investment. A failure to widen access means a foregone improvement in economic productivity and government finance.

6.1. Gender, prosperity and inequality

The test of the formal job hypothesis throws up intriguing findings. Both men and women gain better jobs by using a smartphone to seek information on the internet. Importantly, the increase in the probability of securing formal jobs is higher among women than among men. This is the first nationwide evidence of the gender parity effect of smartphone technology on the productive formal sector participation in Indonesia. Digital technology can also have an equalising effect in other developing countries, given the lower level of women's engagement with the labour market in these countries, thereby bringing the world closer to achieving sustainable development goal 5 on gender equality.

The test of the wage inequality hypothesis draws a more complex picture of inequality. Among women in the formal sector those at the lower points of wage distribution gained higher wages due to smartphone use, and the magnitude of this gain is higher compared to the magnitude accrued to those higher in the wage distribution. The women at the lower rung, with the help of smartphones use, caught up with those at the higher rung.

Among men, comparable gainful effects of smartphone use were also found across the wage distribution. But the effects at different points betray a strong centrifugal force. Together the evidence across gender, jobs and wages paints a complex and rare picture of technology, prosperity and inequality. It invites further work on these issues both theoretically and empirically across the developing countries.

6.2. Technology, inequality and global development (double difficulty with global inequality)

The evidence on technology and inequality uncovered here acts as a springboard to consider issues of global inequality and global development. On the economic rationale of why stark income inequality corrodes the basis for public action, plenty has been said (Stiglitz 2012). In a highly unequal society, those at the top of the income distribution do not share the public priorities of those on the lower rungs, making mobilising support for and prioritising public investment a struggle. Here we add that the character of global inequality takes on a new cultural dimension that makes organising for public action even more difficult.

We are seeing a change in the character of global development through its main protagonists: technology and the highly skilled as the main beneficiaries. Global inequality has stopped being primarily about economic inequality, instead taking on a cultural dimension through changing aversions and aspirations. The skill biased technological change exposition recounted above as applied to developing countries took technological innovations as exogenous and occurring elsewhere in the global technological frontier (Aghion and Howitt 2009, Howitt 2005). For Indonesia and other countries listed in the Overseas Development Assistance, this starting point is empirically warranted. Their share of information and communication technology patents in the European patent office is 0.3% of the OECD countries' over the last quarter century. It is safe to assume that in the short term this starting point needs no modification.

Yet the rising income inequality in Indonesia and many other developing countries has recently afforded their top 0.1% entry to venues frequented by the top earners in the OECD countries (Leigh and Van der Eng 2009). Recall the top forty Indonesians and Americans above. The cream of these developing countries share aversions and aspirations with the cream of Europe and the US Despite the fact that more than 68 million Indonesians in 2009 (Cameron and Olivia 2011), more than the U.K. population, have no access to toilets with running water and must squat when nature calls, the 0.1% share aversions with their European and American peers and would not conceive of using a squat toilet. Global inequality induces shared aversions among the 0.1%.

Their aspirations are also changing. The cream of Indonesia and other developing countries are no strangers to Mayfair and Martha's Vineyard (Hockney 1985). It would not be out of character for the offspring to aspire to a slot in YouTube alongside the Kardashians from the US. In both aversions and aspirations, the cream from developing and developed countries are finding they have more in common with each other than with less advantaged people from their own countries. It is no coincidence that a web application like YouTube (another digital innovation of recent vintage) is a purveyor of aversions and aspirations (President of the World Bank as quoted in the Guardian, 12 April 2017) in this narrative. Technology is not merely the exogenous progenitor but also a cultural purveyor, shaping a cultural distinction between the 0.1% and the rest. In addition to a widening inequality making it difficult to initiate public action such as "toilets for all", the changing character of global inequality make such action doubly difficult since the aspirations and aversions of the 0.1% are untethered and increasingly aligned with the other 0.1% across the globe.

This changing character has implications for global development. It is no longer sufficient to base global income inequality discussions on imputing to all citizens their own country's average income even after the necessary purchasing power adjustments; see Wade. Though convenient, this ignores the cultural distinction arising from the global spread of technology and the attendant inequality. The non-negligible roles of technology in both economic dimension (jobs and wages) and cultural dimension (aversions and aspirations) strengthens the demand for gender parity in digital access and education opportunities. Technology not only helps earn wages but also shape dreams.

A second implication for the study of development is suggested by the theory and evidence here. It is no longer sufficient to study phenomena such as technology and its impact on global inequality from an international development perspective, if this perspective means the developed countries must have the wherewithal to aid the developing countries in responding to challenges, such as rising inequality within countries. The study of global inequality in carbon emissions (an example we owe to David Hulme) can no longer afford ‘us (North) and them (South)’ shorthand (Bidwai 2012) or citizens-to-country imputation. The egregious emitters are found in both developed and developing countries, just as the 0.1% are no longer confined to the developed countries.

7. Conclusion

The results presented here, eschewing simple prosperity or inequality effects, attest to the profound impact of this general purpose technology. Students of innovation have often written about technoeconomic changes wrought by technological innovations of these kinds, as faithfully recorded in the theory and history of technological change (Schumpeter 1934, 1950). Steam power, electricity, digital technologies, and biotechnology are not simply used and adapted by society but they transform society and are equally shaped by it. By requiring future youth to be equipped with coding skills, digital technologies shape curriculum and skill composition in society. Conversely, by neglecting to bridge digital divides, society undermines its ability to actively shape digital technologies to better serve the needs of disadvantaged groups, such as women and people in remote areas. Digital technologies are a double-edged sword capable of conferring dividends and digging divides. By bridging the long-standing social inequalities underlying the digital divides, enhanced opportunities can be created to share more of the digital dividends.

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