# The Role of Micro Data in Understanding Structural Transformation[*]

David Lagakos and Martin Shu

Department of Economics
Boston University

January 2021

## 1. Introduction

It has long been known that economic growth is accompanied by structural transformation of an economy away from subsistence agriculture and into more productive economic activities (Kuznets 1971, 1973). The literature on structural transformation has focused largely on movements of inputs and outputs from agricultural activities to industry and services. Painting with broad brush strokes, these aggregate sectoral shifts do capture much of what economists think of as structural transformation. Yet in recent years, richer micro datasets have become available and allowed researchers to paint a more nuanced picture of how structural change takes place in practice. This essay aims to take a review of this recent literature bringing micro data to bear on structural change, and to highlight additional opportunities for researchers to help shape our understanding of structural transformation and its role in the development process.

Before we begin, it will help to clarify the boundaries of this essay a bit further. We take structural transformation broadly to mean the movement of factors of production, including labour, human capital, physical capital, and land, from less productive economic activities to more productive ones. These movements to more productive activities do not necessarily mean movements out of agriculture per se and can include

[*]This paper was prepared as a Pathfinding Paper for the CEPR-led research programme on Structural Transformation and Economic Growth (STEG), funded by the United Kingdom's Foreign, Commonwealth and Development Office (FCDO) as part of the UK aid effort.

movements within agriculture into more productive type of farming or livestock rearing. By micro data, we mean to discuss individual-, household-, and firm-level data rather than data that have been aggregated to the industry, regional or economy-wide aggregate level.

We focus on micro data that fall into two basic categories. First, there are observational data of individuals, households, or firms, such as the International Public Use Microdata Series (IPUMS) (widely used, for example, in Gollin, Jedwab and Vollrath 2016, Herrendorf and Schoellman 2018, Gollin, Lagakos and Waugh 2014), the Living Standards Measurement Study (LSMS) (as in Alvarez-Cuadrado, Amodio, and Poschke 2020 and Chen, Restuccia and Santaeulàlia-Llopis 2017), the Demographic and Health Surveys (DHS) program (as in Young 2013), and various surveys conducted by researchers independently. Second, we draw on micro data of individuals, households, or firms that have been collected as part of an experiment (e.g. Baird, Hicks, Kremer, and Miguel 2016, Bryan, Chowdhury, and Mobarak 2014, and Baseler 2020) or quasi-experimental in nature (e.g. Sarvimäki, Uusitalo, and Jäntti 2020). These experimental data often consist of baseline and end-line surveys of individuals classified into treatment and control groups. In keeping with the use of micro data, we exclude larger experimental units such as villages, school districts, police precincts, or other geographic areas.

We have organized the rest of this article by economic theme, rather than by taking a chronological approach to the literature on structural transformation.

- In Section 2, we discuss how micro data have shaped research on cross-country gaps in productivity and consumption, with an emphasis on the role of the agricultural sector.

- In Section 3, we discuss how *within-country* gaps in productivity, income and consumption across sectors or space are associated with structural transformation. It is worth noting that studies on rural-urban migration use micro data pervasively and the term is often used alongside structural transformation from agriculture to non-agriculture. The scope of the entire migration literature is too broad for this essay, and we cover only the studies that connect most tightly to structural transformation.[2]

[2] We refer readers demanding a migration narrative to the review by Lagakos (2020), which discusses the size of the urban-rural gap and how internal migration, among other factors, helps to close the gap. We also note that Gollin (2014) provides an in-depth evaluation of the theoretical appeal and the empirical relevance of the dualistic model propelled by Lewis (1954), a way of thinking about structural change that still influences many researchers nowadays. For a more general review of the literature on rural-urban migration, see Lucas (2015).

- In Section 4 we focus on how the structure of labour markets differs with the level of development, and the role of micro data in informing us how labour market outcomes vary systematically with development.

- In Section 5, we review the literature on how land markets shape productivity and structural transformation, and the related policy issues in developing economies. At the forefront of this discussion is the issue of whether land is misallocated across farmers, and to what extent policy reforms in land markets could raise productivity and encourage structural change.

- Section 6 lists efforts to document and explain patterns of structural transformation not focusing on the conventional order of labor reallocation from agriculture to industrial production, then to services. In particular, we discuss transformation within agriculture and the lack of industrialisation during structural change.

- Section 7 discusses how micro data have given us a sharper perspective on the role infrastructure plays on structural transformation.

- Section 8 concludes this essay with discussions about other research topics we see as under-explored, potential improvement in data collection efforts, and methodological considerations of how to engage field experiments in the macro development literature.

The careful reader might have noticed that we do not have a section for capital as we do for land and labour, despite the central role of capital in modern production. The reason is that good-quality data on capital at the micro level is scarce. We discuss this issue in the last section and note that richer micro data on capital would be a valuable resource for future research.

## 2. Cross-Country Gaps in Productivity and Consumption

One broad motivation for studying structural transformation is to address the huge *cross-country* differences in aggregate productivity between rich and poor countries. Researchers have generally attempted to account for these aggregate differences by looking at sector-level productivity, typically divided as agricultural and non-agricultural sectors. Restuccia, Yang, and Zhu (2008) and Herrendorf and Valentinyi (2012) find with cross-country aggregate data that low labour productivity and high share of employment in agriculture are responsible for, in an accounting sense, the low aggregate labour productivity in poor countries. A shocking comparison is that the agricultural labour productivity in the richest countries can be 78 times higher than that in the poorest, whereas the non-agricultural disparity is only around five. Caselli (2005) shows that the differences in sectoral shares of agriculture and non-agriculture across countries can account for around two thirds of the observed cross-country total factor productivity (TFP) gaps, and that the differences in GDP per worker would virtually disappear if poor countries had the same agricultural labour productivity as the US. Using a development accounting framework, Vollrath (2009) shows that factor market inefficiency can explain nearly three quarters of the aggregate TFP variations and around one third of the variation in income per capita between countries, attributing a considerable fraction of cross-country productivity differences to misallocation.

The use of micro-level data in recent years has greatly improved the measurement of some economic variables of concern and enabled us to revisit questions such as what explains the cross-country agricultural productivity gaps and how agricultural technology facilitates structural transformation. For example, Caunedo and Keller (2021) use data of retail prices, ages, manufacturers, hours used per year, and horsepower of tractors across 16 countries between 2007 and 2017 to construct a measure of the quality of agricultural capital stock. They find that adjusting for capital quality increases the importance of capital in accounting for the cross-country productivity difference in agriculture from 21 to 37 percent.

Donovan (forthcoming) offers a micro foundation for the observation made by Restuccia, Yang, and Zhu (2008) that farmers in poor countries use fewer intermediate inputs. He argues that farmers in low-income countries intentionally choose not to use intermediate inputs in order to reduce their exposure to uninsurable shocks. Disciplining the risk parameters with household level harvest data from India, his model explains one-third of the difference in the use of intermediate inputs in agriculture between India and the US. Adamopoulos and Restuccia (2018) use remote sensing data combined with potential and actual yields from the Global Agro-Ecological Zones project and find that the cross-country agricultural productivity gaps are not due to heterogeneous endowment in land quality.

Bustos, Garber, and Ponticelli (2020) explore a channel of capital flow through which agricultural technology shocks facilitates structural transformation. They show that the spread of genetically engineered soybean seeds in Brazil increases the level of savings and benefits the industrial and service sectors in regions more financially integrated with the soy-producing areas, using branch-level data of bank deposits and loans. The micro-level impact realises in the way that firms with preexisting relationships with banks receiving funds from the soy-producing areas experience faster growth in borrowing and employment.[3]

## 3. Within-Country Gaps, Sorting, and Mobility Barriers

A greater body of the literature approaches structural transformation by looking at *within-country* gaps between sectors or regions. An old debate in this literature is whether these gaps are more of a result of workers sorting efficiently into different sectors/areas or a result of misallocation due to reallocation costs. In this section, we discuss recent studies contributing to this debate using micro data.

Gollin, Lagakos, and Waugh (2014) draw on household survey data for 151 countries of all income levels to account for the large gaps in value added per worker between the agricultural and non-agricultural sectors, which they dub the *agricultural productivity gap*. They measure sectoral differences in hours worked and human capital per worker (approximated by education attainment) and show that higher average hours worked and greater human capital in the non-agricultural sector accounts for around one third of the agricultural productivity gaps on average. In the developing world, their adjustments account for around half of the gap. McCullough (2017) argues that the hours-adjusted gaps are even smaller in the poorest countries (Ethiopia, Malawi, Tanzania, and Uganda). The non-agricultural sector is only 1.4 times more productive than the agricultural sector in these four countries in per hour terms, compared to much larger unadjusted gaps. These results suggest that reallocating labour out of agriculture may not buy us as much improvement in the aggregate labour productivities of low-income countries as one would expect by looking at the raw per-worker gaps.

There is a common worry, however, that the gaps in labour productivity may be problematic as agricultural value added is not well measured. Herrendorf and Schoellman (2015) observe that agricultural value added is severely under-estimated in the US, and argue that it is more appropriate to measure marginal product of labour with average wages than with value added per worker. Their results show that the gaps measured in income are much smaller, weakening the claim that large gaps in productivity imply severe misallocation of labour. Related work by Vollrath (2014) and Herrendorf and Schoellman (2018) both draw on detailed micro survey data to measure

[3] Although aggregated to the municipal level, the data used in a parallel study by Bustos, Caprettini, and Ponticelli (2016) demonstrate how data of predicted yields can be useful in informing us about the exposure to benefits of new technologies, hence evaluating the effects of different types of technological advancement on structural change. Similar use of the data can be found in Bazzi, Gaduh, Rothenberg, and Wong (2016) where the authors find that individual agricultural skills may be tied to agroclimate conditions, which induces persistent regional gaps in agricultural productivity.

sectoral gaps in wage rates and income. These studies explore richer heterogeneity among workers by estimating the Mincerian returns of human capital measured by education and experience, and successfully bring the gaps further down. Nevertheless, they note that the adjusted wages are still lower in agriculture even with an entire set of control variables.

Related to agricultural productivity gaps are the urban wage premia, measured as the premium of wages in cities over villages (or rural areas more generally). Using micro level data from high- and middle-income countries, researchers have documented that the *urban wage premium* manifests not only through the level of wages, but also through the returns to experience. Glaeser and Maré (2001), de la Roca and Puga (2017), Rivera-Padilla (2020a), and Eckert, Hejlesen, and Walsh (2020) are several examples that document this fact in the US, Spain, Brazil, Mexico, and Denmark. The unadjusted premium averages around 30% and does not fall much when adjusted for education and experience.[4] Faster sorting of workers towards the type of establishments, occupations, and industries typically found in cities accounts for the vast majority of this urban wage growth premium. The additional value of experience persists even when workers leave big cities and is stronger for those with higher initial ability.

Enormous gaps also exist when measured in consumption, with a rural-urban divide in most cases. A key challenge of this approach is price deflation, as many goods and services are not easy to compare between cities and villages. Ravallion, Chen, and Sangraula (2007) set a nice example for building rural-urban price deflators using spatial price data calculated from household surveys conducted by World Bank in a large set of developing countries. Based on the real consumption measures derived with those deflators, the authors find stark regional differences in the distribution of poverty over rural and urban areas. The fraction of people under the “$1 a day” poverty line at 1993 international price level varies between nearly 60 percent in Latin America and below 10 percent in East Asia. In terms of trends, Africa, the Middle East, and Latin America have seen an increasing percentage of the poor in their cities, while Eastern Europe and Central Asia have seen the opposite.

Young (2013) employs a different approach that measures real consumption in kind to circumvent the price discrepancies in rural and urban areas. The idea is to infer real consumption from cross-sectional correlations between education attainment and the consumption of each “good” measured in the data. The DHS surveys used in this

[4]Instead of applying the rural-urban dichotomy, Chauvin, Glaeser, Ma, and Tobio (2017) examine the gaps in terms of the response of real wage to population density. They find that the wage-density elasticity in China and India almost triples that in the US.

research ask interviewees questions about their ownership of durable goods (e.g. televisions and cars), housing condition (e.g. access to electricity and tap drinking water), employment status (whether in school or working), family economics (whether married or having given birth in past year), and children's health outcomes, reflecting real living standards comparable across countries and time. Young (2013) uses these data from 65 developing countries in the DHS to construct the real consumption measure and finds that the urban-rural gap accounts for 40 percent of the cross-country inequality in real consumption. He also presents a model that illustrates how the gap can be explained qualitatively by spatial sorting of skilled and unskilled workers.

To take further advantage of micro data, researchers turn to panel surveys that track the same individuals across time. As wages and consumption of workers who reallocate are recorded, it becomes possible to control for unobservable worker characteristics that may affect the sectoral gaps. For example, Hamory, Kleemans, Li, and Miguel (forthcoming) find that accounting for individual fixed effects reduces up to 90 percent the wage gap between agriculture and non-agriculture, using panel survey data from Kenya and Indonesia that span over a decade. Their findings suggest extensive selection effect across sectors, which implies that policies encouraging workers to move out of agriculture would only induce marginal gains. Lagakos, Marshall, Mobarak, Vernot, and Waugh (2020) extend the analysis with consumption data from panel surveys in six developing countries, including Indonesia. They confirm that the urban-rural gaps in consumption are significantly reduced once individual fixed effects are included. On the other hand, they also note that moving to urban areas still increases average consumption by 26 log points from the perspective of a potential migrant.[5]

As many reduced-form studies mentioned above interpret their results as suggestive evidence of workers self-selecting into different sectors based on unobservable skills, illustrating the quantitative significance and counterfactual outcomes of the sorting mechanism requires a micro-founded structural model. Applying the Roy model as in Lagakos and Waugh (2013), a number of subsequent studies supplement evidence on the relevance of the selection mechanism. Alvarez (2020) shows that selection explains the inter-sectoral wage gap as well as its evolution along the time dimension in Brazil, with the model calibrated to Brazilian household surveys. The study mentioned earlier

[5] Much of the gains from migration may involve moving to peri-urban areas or secondary cities, rather than to the capital or to mega cities. Christiaensen, de Weerdt, and Todo (2013) use the LSMS panel data tracking more than 3,300 individuals in rural Kagera, Tanzania between 1991 and 2010 to show that around half of the individuals who exited poverty did so by moving out of agriculture into the rural nonfarm economy or secondary towns, instead of big cities. Only one out of seven exited poverty by migrating to big cities. Meuller, Schmidt, Lozano, and Murray (2019) reiterate this finding by emphasising the role of what they call peri-urban areas in labour reallocation, as these areas offer prospects for diversification out of agriculture with lower moving costs and job-search frictions than urban centers.

by Herrendorf and Schoellman (2018) concludes that selection explains the income gap between agriculture and non-agriculture better than barriers to labour reallocation. Pulido and Święcki (2019) also run a horse race between self-selection and barriers to migration based on Indonesia Family Life Survey. They confirm the importance of the selection effect, but also point out that barriers to migration may hold back 35 percent of reallocation and as much as 21 percent of aggregate output gains.

Not all studies agree that positive selection can account for much of the sectoral gaps. Miguel and Hamory (2009) assess the effect of the deworming treatment in Kenya on human capital and migration decisions and find that accounting for the selection effect does not explain much of the urban-rural wage gap in Kenya. Alvarez-Cuadrado, Amodio, and Poschke (2020) draw on rich panel data on farm households using LSMS data for Ethiopia, Malawi, Nigeria, and Uganda, and find evidence that suggests negative selection out of agriculture, a pattern opposite to typical findings in the literature with data from richer countries. Specifically, they find that reallocation from agriculture to non-agriculture concentrates on farmers with higher agricultural productivity. Their findings remind us that the details of the selection framework still await more careful study.[6]

On the other hand, a growing body of evidence has highlighted how barriers to reallocation impede structural transformation. For example, Hobijn, Schoellman, and Vindas (2018) and Porzio, Rossi, and Santangelo (2020) find that about half of structural transformation relies on new cohorts entering disproportionately into growing industries, implying considerable reallocation costs within cohorts. Porzio, Rossi, and Santangelo (2020) compiles a comprehensive list of education policy around the world and argue that the accumulation of non-agricultural skills through education attainment is the main driving force of the reallocation pattern by cohort. Skill requirements, in other words, are a key barrier for structural change.

Clean identification of reallocation frictions, however, asks for more than observational data, since the results could be difficult to interpret when the decision to reallocate is not entirely a response to higher gains or lower costs alone. Worker heterogeneity in both the costs and benefits of reallocation obscures accurate measures of the net gains when identification relies only on migration. Moreover, the common assumption that people actively choosing the best places or sectors for themselves is challenged when certain decisions are forced due to factors like involuntary job loss.

[6] Jones, D'Aoust, and Bernard (2007) draw on panel surveys from Nigeria, Tanzania, and Uganda. The authors find the urban wage premia in these countries comparable to those in the richer countries and not well explained by spatial sorting

To address this issue, researchers have taken advantage of field experiments that assign exogenous incentive to migrate. For example, Baseler (2020) finds with two field experiments in Kenya that, although urban workers earn twice as much as rural workers, underestimation of urban incomes significantly impedes rural-urban migration. Informing villagers about the wages and food prices in the capital city and other urban centers has a large and lasting positive effect on migration. The underestimation of urban wages is due partly to migrants underreporting their income in cities. To minimise remittance obligations, those who migrate have an incentive to hide their true level of income, leading their parents to underestimate urban income by nearly half. Once correct information about urban earnings is provided, migration to the capital city increased by 33% over two years.

Munshi and Rosenzweig (2016) and Morten (2019) discuss how the lack of insurance markets serves as a type of frictions that prevents efficient spatial allocation of labour. The idea is that the lack of formal insurance in rural areas forces many people to rely on the informal risk-sharing networks formed in the local community, to which one loses access upon migration. Males in relatively wealthy households within a caste, who tend to benefit less from the network, are more likely to move, while males in households facing greater rural income shock, who tend to benefit more from the network, migrate less. Counterfactual simulations in Munshi and Rosenzweig (2016) predict that improving insurance markets could substantially mitigate the misallocation of rural workers.

Another type of frictions at work may be borrowing constraints. Bryan, Chowdhury, and Mobarak (2014) run a randomised controlled trial in rural Bangladesh that offered a conditional cash transfer for seasonal migration to encourage 1,292 landless households to move to nearby cities. This conditional migration transfer induced 22 percent of treated households to send a seasonal migrant relative to a control group that got no subsidy. Treated households were still more likely to re-migrate after the incentive is removed. Overall, households that send a migrant experience sizable consumption increases of around 30 percent per household member. Akram, Chowdhury, and Mobarak (2018) expand on this experiment to randomise transport subsidy across 133 villages for 5,792 potential seasonal migrants. The subsidies significantly increase the emigration rate, agricultural wage rates, and available work hours in the village. Households that sent migrants experienced similar sized consumption increases as in Bryan, Chowdhury, and Mobarak (2014), and migrants experienced substantially higher labour income. At face value, these studies seem to confirm that migration risk and borrowing constraints play a big role in discouraging migration.

A structural revisit to the experiments questions the relevance of borrowing constraints in this context. To better understand the mechanism at work in the experiment, Lagakos, Mobarak, and Waugh (2020) build a dynamic structural model of migration that they calibrate to replicate the experimental findings in the two studies. The calibrated model reveals substantial disutility of moving and that the subsidies are more likely to induce migration from individuals with *low* consumption and asset levels. They draw from the implication of the model that the welfare effects of migration subsidies arise through better insurance for vulnerable rural households rather than by relaxing credit constraints for those with high urban productivity but who are stuck in rural areas. In other words, rural households strongly prefer to stay in rural areas and migrate to cities only when the gains are so large that offset the disutility of moving.[7]

We have discussed in this section how various within-country gaps are measured and explained by sorting and reallocation barriers. A key message from the literature is that the observed gaps cannot be solely the result of sorting. Substantial barriers are at work since we observe sizable gains in income upon induced migration. In addition to the barriers we discussed, there are certainly other frictions awaiting to be identified and measured. On the other hand, more investigation on the quantitative impact of those frictions on macro development outcomes such as aggregate productivity will also be valuable. Lastly, we note that sectoral reallocation and rural-urban migration have both conceptual and substantial differences, although the line often blurs in the discussion of structural transformation. Pulido and Święcki (2019) find that most (but not all) of the urban-rural income gaps in Indonesia can be explained by the sectoral composition and non-agricultural premium. Whether this is a common pattern across countries awaits more empirical evidence.

## 4. Structural Transformation of the Labour Market

Labour market outcomes vary systematically with the level of development. For example, is widely known that low-income countries have much higher self-employment than rich countries (see, for example, Gollin 2008). Several recent efforts utilising micro data have shed new light on the structural differences in labour market

[7] Kleemans (2015) presents a model that distinguishes the two types of migration – one to cope with negative income shocks and the other to invest for higher future income. This distinction is supported by data from the 20-year panel of Indonesia that migration after negative shocks tends to be temporary, aims for rural destinations and is more likely undertaken by low-wealth individuals, while investment migration is more likely to target urban destinations, occur over longer distances, and span a longer duration.

activities that separate rich and poor countries. In this section, we present the most recent findings connecting structural transformation and labour market outcomes.

A standard assumption in the macroeconomics literature is “balanced growth preferences” that feature no long-run changes in average hours worked in response to productivity growth. Indeed, this assumption provides a reasonable fit for the aggregate US data in the post-war era (see e.g. King, Plosser, Rebelo, 1993). Yet looking back over the last century and a half, Ramey and Francis (2009) find declining aggregate hours, particular in the early part of the 20th century. Boppart and Krusell (2020) draw on historical data from European countries to show that hours worked have been declining steadily by a little below half a percent per year in 25 high- and middle-income countries back to the 1870s.

Looking in the cross-section of countries today, Bick, Fuchs-Schüdeln, and Lagakos (2018) document that average hours per adult are about 50 percent higher in the world’s poorest countries than in the world’s richest. At the individual level, hours worked are also decreasing in wages for most countries except for a flat or increasing relationship in the richest countries. Bick, Fuch-Schündeln, Lagakos, and Tsujiyama (2020) follow up on these observations and second the explanation by Boppart and Krusell (2020) that the income effect on leisure serves as a main driving force of the decline of average hours worked, with higher taxation and transfers being the alternative. Central to their story is the structural transformation of labour markets from primarily self-employment in poorer countries to market wage work in richer ones.

Related to the higher working hours in developing economies are lower unemployment rates. Feng, Lagakos, and Rauch (2021) find that this pattern is driven largely by the high unemployment rates of low-educated workers in rich countries. High-educated workers have unemployment rates that exhibit very little variation with GDP per capita. The authors interpret these facts in a model with a frictional “modern” labour market and a traditional self-employment sector. As an economy develops, and modern productivity rises, workers move from traditional self-employment to the modern sector. Many modern sector workers lose jobs each period and are cast into unemployment. The model and facts in this paper point to a world where labour markets, and the resulting unemployment, come along with development. Unemployment per se is therefore not a sign of under-development, but a sign of more developed market activities.

Poschke (2019) emphasises labour market frictions in accounting for rising unemployment rates with income across countries. IPUMS micro data reveal that poor countries have high rates of unemployment relative to wage employment, and the level of self-employment is high particularly where the unemployment-wage employment ratio is high. The author explains this pattern with a model in which labour market frictions push workers into low-productivity self-employment. The quantitative model calibrated separately to eight countries shows that the labour market frictions can explain almost all variation in unemployment, wage employment, and self-employment. The lesson is that higher labour market frictions may be an important reason why so many workers are forced into self-employment in low-income countries.

Closely related to the transition from self-employment to wage employment is the shift from home to market production, which often entails increasing participation of women in the formal sector. Ramey and Francis (2009) document that hours worked by men in the US has declined over the past century but were almost fully compensated by increasing hours from women. Ngai and Pissarides (2008) present a theory of time reallocation between home and market production that rationalises this pattern, emphasising the role of biased TFP growth rates favouring market production over home production for manufacturing and services. Ngai and Petrongolo (2017) argue that the comparative advantage of women in services leads to the rise in women's relative wages and market hours as structural transformation drives marketisation of services. Buera and Kaboski (2012) infer from the sectoral differences in the size of establishments that technologies favouring scale production lead to industrialisation and marketisation of services at the same time.

Erosa, Fuster, Kambourov, and Rogerson (2017) build a Roy model of occupation choice that matches the distribution of hours worked across genders and occupations. The authors document a positive correlation between hours and wages across occupations and the disproportional representation of women in low-hours occupations. Quantitatively, misallocation of labour due to the higher burden on women in home responsibilities implies significant aggregate effects on productivity and welfare. It is worth pointing out that most studies treating the differential labour market outcomes by gender focus on the US data. Therefore, a gap to be filled concerns the extent to which the patterns discussed in this paragraph can be generalised to the rest of the world, especially in developing economies.

One important aspect of labour market outcomes is the flow of workers between jobs. Cross-country comparisons of labour market flows have been hindered by the availability of data until recently. Donovan, Lu, and Schoellman (2020) take a heroic effort to compile a dataset of rotating panel labour force surveys from 42 countries and successfully matched over 66 million observations. With this dataset, they document that labour market flows (job-finding rates, employment-exit rates, and job-to-job transition rates) are two to three times higher in the poorest countries than in the richest ones. The high volume of flows is mainly driven by high separation of workers with low tenure. In addition, tenure has a much stronger effect on wage growth than experience in poorer countries. The authors show that these facts are consistent with models of job ladders and employer learning. From the perspective of structural change, the message here is that labour market relationships in low-income countries may be very short lived on average compared to richer economies.

The structural transformation of labour markets is closely related to the structural transformation of occupational structure. Duernecker and Herrendorf (2016) compile census data for the majority of the world population and document that the share of service occupations rises in all sectors. They show that uneven technological progress based on occupations can explain such pattern. Bárány and Siegel (2020) reinforce the point that the bias in technological change across occupations plays a much more important role in labour reallocation than sector-biased technological change.[8]

The broad lesson in this section is that micro data have played a central role in characterising how the structure of the labour market transforms with development. This data shows that individuals in developing countries work longer hours on average, are less likely to be unemployed, are more likely to be self-employed and informally employed, and have more transitory wage jobs compared to their counterparts in developed countries. The different trends in the labour market outcomes by gender play a role in explaining some of these observations. Recent efforts in compiling panel data across countries and the rising emphasis on the role of occupations point towards promising potential for future research. The role of labour market frictions and labour market policy in structural transformation are still very much open issues for future studies to pursue.

## 5. Land Markets, Land Reforms, and Land Misallocation

The land market is arguably just as important as the labour market for its role in agricultural production. In previous years, much effort has been devoted in the

[8] Bustos, Castro-Vincenze, Monras, and Ponticelli (2020) use Brazilian social security data to measure labour input in innovative occupations. They find that the expansion of low-R&D industries, induced by new agricultural technology, attracted workers away from innovative occupations in high-R&D industries and slowed down local manufacturing productivity growth. This finding is rationalised with a multi-sector growth model in which only skill-intensive manufacturing innovates and generates knowledge spillovers. As most workers leaving agriculture are unskilled, they enter the non-innovating industries that align with their comparative advantage, which in turn pulls skilled workers from the innovative industries due to complementarity between skilled and unskilled workers in production. Long-run growth, therefore, can be sacrificed in response to shocks that improve short-run outcomes through a mechanism that highlights occupational characteristics.

economics literature to identifying potential land misallocation and evaluating land reforms around the world. The use of large-scale micro data, however, was not very common until the recent decade, with the exception of the Farm Management Studies of India.[9] Numerous earlier studies use data at the aggregate or regional level to argue for or evaluate land reforms. For example, Rosenzweig (1978) models the Indian land market to argue that a redistribution of land from large- to small-farm households in India would significantly raise agricultural wages and benefit landless households. Besley and Burgess (2000) use state level panel data from India and find that the large volume of post-independence land reforms is associated with poverty reduction in rural India, while urban poverty is not affected. Otsuka (1991) works with village level data and finds that the success of the 1972 land reform in Philippine is associated with technical change, represented by the adoption of modern seed-fertiliser technology.

The use of micro data in recent years has enriched our understanding about how land markets facilitate productivity growth and structural transformation and provided better grounds for policy evaluations. One popular source of data in this literature is the Living Standards Measurement Study (LSMS), a data effort led by World Bank in cooperation with governments around the world. We begin our discussion with several studies that rely on this longitudinal dataset.

Restuccia and Santaeulàlia-Llopis (2017) use the data from Malawi and find that the size of farms and the use of capital are unrelated to farm TFP, which reveals substantial misallocation in the agricultural sector. They show that completely removing misallocation would boost farm TFP by a factor of 3.6. The gains would be more than twice as larger for farms operating on non-marketed land, which accounts for 83% of farms in Malawi, than farms having access to marketed land. Using another set of LSMS surveys from Ethiopia, Chen, Restuccia, and Santaeulàlia-Llopis (2020) observe from a land certification program that land rentals substantially reduce misallocation and increase agricultural productivity. In similar spirit, Deininger, Savastano, and Xia (2017) argue that land market has great potential to increase land productivity in light of large gaps in land endowment and productivity, using LSMS data from six countries in Africa. Utilising household surveys from Vietnam, Nguyen, and Warr (2020) find that land consolidation, treated as labour-augmenting technology, raises both farm productivity and farm income and stimulates increased machinery use. It also reduces farm labour supply, lowers labour intensity in farming, and thereby releases more farm labour to off-farm employment.

[9] Early surveys, however, are subject to severe sample selection bias. See Carter (1984).

Empirical observations from China also illustrate how misallocation affects farm productivity. Jin and Deininger (2009) use a household level panel to illustrate the large contribution of land markets to occupational diversification and the productivity of land. Their model suggests that transferring potentially idle land from less able but more affluent households who joined the non-farm sector to poorer ones with ample family labour not only facilitates non-agricultural growth, but also leads to significant productivity gains. Adamopoulos, Brandt, Leight, and Restuccia (2020) find with another household panel dataset from China that distortions in the allocation of land and capital significantly affect the observed distribution of farm TFP. Furthermore, institutions generating the misallocation may have a particularly negative effect on more highly skilled farmers. Eliminating such distortion can have large impacts on agricultural productivity. Studying an example of restricting land reallocation, Zhao (2020) finds that a reform in 2003 that stopped land reallocations in all Chinese villages on average increased off-farm labour and household per capita net income by 7% and 6.5% respectively, at the cost of 6% reduction in total agricultural output and significant increase in intra-village income inequality.

Other studies are somewhat more skeptical about the importance of misallocation of land and labour in the agricultural sectors of low-income countries. Using LSMS detailed plot-level data from household panel surveys collected in Tanzania and Uganda, Gollin and Udry (2019) estimate a model that allows for several kinds of measurement error and heterogeneity. They find that measurement error and heterogeneity together account for a large fraction of the dispersion in measured productivity, which suggests that the potential for efficiency gains through reallocation of land may be relatively modest. The effect of better land institution on capital and investment also differs. While Deininger and Jin (2006) find with an Ethiopian farm households survey that the right to transfer land unambiguously enhances agricultural investment, Deng, Yan, Xu, and Qi (2020) find with Chinese rural household data that improved land security does not affect the adoption of agricultural machineries.

One policy that may be at work in misallocating inputs in the farm sector is restricting farm size. Adamopoulos and Restuccia (2014) calibrate a quantitative model of heterogeneous farm size to US farm-level data and show how farm size ceiling and progressive land tax adversely affect farm size and productivity. Adamopoulos and Restuccia (2020) compute that the land reform in Philippine imposing a ceiling on land holdings reduces agricultural productivity by 17 percent. With nationally representative survey data from Sri Lanka, Emran and Shilpi (2015) explore a natural experiment where historical malaria played a role in shaping land policy. They find that land restrictions increase wage employment in agriculture but reduce it in manufacturing and services, with no perceptible effects on non-agricultural self-employment.

Interestingly, many policy reforms are able to induce labour reallocation out of agriculture by just reinforcing private land ownership without forcing any redistribution of land. Using an eight-year panel of 1,200 households in six Chinese provinces, Deininger, Jin, Xia, and Huang (2014) find that land tenure insecurity discourages households from quitting agriculture, while the recognition of land rights through formal certificates increases participation in non-agricultural labour markets through encouraging temporary migration of rural labour. Gottlieb and Grobovšek (2019) and de Janvry, Emerick, Gonzalez-Navarro, and Sadoulet (2015) study similar reforms in Ethiopia and Mexico that abolish the "use it or lose it" principle. They find that the reforms encourage sizable labour reallocation into non-agriculture. Moreover, the program in Mexico led to land consolidation and demonstrates more efficient resource allocation. Agyei-Holmes, Buehren, Goldstein, Osei, Osei-Akoto, and Udry (2020) employ a regression discontinuity design combined with household panel surveys to evaluate a pilot land titling intervention in Ghana. The program does not induce more agricultural investment or credit taking among treated households. Instead, they respond by diversifying into nonfarm activities, just like what scholars find with similar programs in other countries.

Beg (2019) studies a subtler innovation of digitising rural land records in Pakistan. Although not a direct reform on any policy that affects land allocation, improved security to land titles makes landowning households more likely to rent out land and shift into non-agricultural occupations. Evidence suggests that allocative efficiency is improved as land is cultivated by more productive farmers. These observations add to the literature that land market frictions, particularly insecure ownership, present a constraint to scale farming and structural change in developing countries.

Land reforms may also have intergenerational effects on structural transformation. Galán (2018) explores the 1968 agrarian reform in Colombia which expropriated low-productivity land and redistributed the land to eligible applicants evaluated with a scoring system. The author matches the applicants and their children in administrative data and studies the effect of receiving land on the children based on a regression discontinuity design around the score cutoff. He finds that the children of land recipients in reform exhibit higher intergenerational mobility, have better living standards, and are more likely to work in formal and high-skill sectors.

The studies discussed in this section highlight the prominent role of land ownership in facilitating structural transformation. Although policy reforms improving the security of land ownership does not necessarily induce more agricultural investment, the encouraged reallocation of labour and land undoubtedly enhances labour productivity and income. Future work should continue to explore the way improving land markets can serve as an instrument for facilitating structural transformation.

## 6. Structural Transformation without Industrialisation

A central challenge for the structural transformation of poor economies is to pull farmers out of subsistence agricultural production. This process, however, need not involve labour reallocation from rural farms to urban factories. In fact, the kind of massive reallocation of labour into organised modern industries in the wake of the industrial revolution or during the take-off of post-war eastern Asian economies is not observed in many parts of the world despite their economic growth. In this section, we focus on two types of structural transformation that do not emphasise the role of industrialisation – agricultural transformation that engages farmers in more productive agricultural activities, and labour reallocation into the service sector directly.

The growth in income and productivity in the agricultural sector has contributed a lot to the growth in Africa. Christiaensen and Kaminski (2015) show with household panel surveys of Uganda that about two thirds of poverty reduction was driven by households continuing to spend most of their time in agriculture, while the remaining one third by those diversifying into the non-farm economy but staying in rural areas. Wineman, Jayne, Modamba, and Kray (forthcoming) draw on LSMS data from Tanzania to show that medium-scale farms and commercialised farms are taking up a larger share in Tanzanian agriculture over the period from 2008 to 2014. Farmers are using more modern intermediate inputs, participating more in land and labour markets, and relying increasingly on agricultural product markets.

One driving force of such agricultural transformation can be better access to technology and capital. Takeshima and Liu (2020) use household level data in Nepal and Ghana and find that households in areas more exposed to yield-enhancing seed technologies are more likely to mechanise their agricultural production. Using household surveys from two districts in Northern Ghana, Mueller, Masias, and Vallury (2019) find that access to motorised tricycles allows more farming households to engage in production of agricultural goods of higher value, utilising the time saved from transferring crops from plots to homestead.

Another mechanism to induce the transformation is through reduction of trade costs. Using detailed data from Mexican farms, Rivera-Padilla (2020) shows that most farmers grow staple crops, despite the fact that labour productivity in cash crops is substantially higher. He argues that higher trade costs of cash crops force farmers to grow staple crops for themselves and prevent them from specialising in cash crops.[10] Simulation of a quantitative model shows that reducing trade costs in Mexico to the US level would raise the ratio of employment in cash crops to staples by 15 percent and generate a 13 percent increase in agricultural labour productivity.

The role of manufacturing industries in structural transformation may not be as prominent in developing countries nowadays as it used to be in most of today's advanced economies. Gollin, Jedwab, and Vollrath (2016) examine the sectoral compositions of cities using micro data from 88 countries and note that urbanisation involves two very different types of cities. Economists have conventionally paid more attention on "production cities" that depend on manufacturing in industrialised countries and cared less about "consumption cities" that consist mostly of non-tradable services in resource exporting countries. They point out that Africa and the Middle East serve as perfect examples of urbanisation without industrialisation. Diao, Harttgen, and McMillan (2017) also document that the structural transformation in Africa lacks significant expansion in manufacturing employment, using Groningen Growth and Development Center's Africa Sector Database (de Vries, Timmer, and de Vries 2015) and the Demographic and Health Surveys.

The following studies take closer looks at this pattern in specific countries. Resnick and Thurlow (2014) document that the structural transformation accompanying the growth episode of Zambia from 1991 to 2010 lacks the creation of high-quality formal jobs, while at least two thirds of the population are still stuck in agriculture. Informal trade contributed most to employment growth, while manufacturing continued to decline. Fiorini and Sanfilippo (2019) find that better roads in Ethiopia reduce the share of agricultural workers and increase that of workers in the services sector but not in manufacturing. Summarising data from the National Baseline Survey Report for Micro, Small, and Medium Enterprises of Tanzania, a comprehensive nationally representative survey covering three million enterprises, Diao, Magalhaes, and McMillan (2018) show that trade services take up an overwhelming 80 percent of the firms in the sample, whereas manufacturing accounts for less than 15 percent. Emerick (2018) finds that

[10] Gollin and Rogerson (2014) make similar points with their quantitative model calibrated to the aggregate level data from Uganda.

temporary positive agricultural productivity shocks release surplus labour from agriculture to local service industries in rural India.

Although many episodes of development without industrialisation have been documented, we still know very little about the exact forces behind the observations and the implications for future growth in these countries. More investigations on this topic may help not only clarify the economics, but also inform policy makers about feasible growth strategies.

## 7. Infrastructure and Structural Transformation

The importance of infrastructure on economic growth has long been recognised and studied. Examples of earlier research include Aschauer (1989) who pioneered the use of econometric methods in estimating the benefits of infrastructure projects, especially highways, streets, water systems, and sewers, using aggregate data from the US. Baxter and King (1993) are among the first who employ structural approach to think about the efficacy of government spending in general equilibrium. More recently, Röller and Waverman (2001) use data from OECD countries and find a causal relationship between telecommunications infrastructure and aggregate output. Though identifying the effect of infrastructure on development is challenging using aggregate data, and precise mechanisms are harder to uncover.

In recent years, rich micro data sets have helped identify and assess the impact of infrastructure on structural transformation. For example, a large-scale village road program in India has inspired a number of studies with high quality micro data. Aggarwal (2018) finds that market access caused rural households to increase the use of agricultural technologies and pull teenaged members out of school to join the labour force, exploring variation in the timing and placement of the paved roads. Asher and Novosad (2020) use a fuzzy regression discontinuity design with household and firm census data and find that new roads facilitate the movements of workers out of agriculture, and the effect is concentrated among males and households with low levels of land. Shamdasani (2016) finds that households who gain access to the improved roads diversify their crop portfolio, increase the use of inputs, intensify labour hiring, and enter the sales of farm output.

Infrastructure projects do not only lead to structural transformation with their first-order effects. Brooks and Donovan (forthcoming) combine household surveys and telephone interviews to study the effect of new bridges in rural Nicaragua that eliminates the uncertainty of access to market due to seasonal flash floods. They find that flash floods decrease labour market income by 18 percent when there is no bridge, and such an effect disappears with the presence of a new bridge. To evaluate the welfare implication, they calibrate a quantitative model and find that the welfare gain is much larger than the increase in income brought by the bridges. This study undoubtedly provides a new perspective on how we understand the benefits of infrastructure projects.

Other than roads, access to stable electricity can also encourage structural transformation for its role in industrial production. Gaggl, Gray, Morinescu, and Morin (2021) use full count historical census data of the US from 1910 to 1940 to identify the effect of the expansion of high-voltage electricity grid on structural transformation, utilising an instrumental variable approach based on favorable geographic characteristics for electrification. The authors infer from their results that the electrification episode can account for around 20 percent of the decline in agricultural employment and the rise in manufacturing employment.

The several papers we discussed have shown a variety of channels through which infrastructure projects affect structural transformation, including reducing market frictions such as trade costs, mitigating income volatility, and granting access to new production technologies. We believe that a lot more can be expected with the increasing use of micro-level data. For example, survey data from firms can provide micro-founded estimations for structural models, such as the one in Fried and Lagakos (2020) that calculates the long-run TFP gains and potential expansions of modern industries in Africa from eliminating electricity outages. In addition, potential effects by new types of infrastructure in the information era such as internet and smartphone networks remain a blue ocean to be explored.

## 8. Perspectives on the Path Forward

This essay has highlighted the important role that micro data has played in better understanding structural transformation. In the coming years, we are sure to see more questions being answered, as increasingly better micro data sets become available. In this concluding section, we offer some perspectives about the use of micro data in the research of structural transformation, focusing on the questions to be studied, the data to be collected, and the methods to be used.

There are important questions in the literature that are (to our knowledge) yet to be addressed with micro data. For example, a small but growing strand of literature has started to document the heterogeneity in growth patterns within the service sector. Jorgenson and Timmer (2011) and Duarte and Restuccia (2020) study advanced economies and are among the first to study the substantial differences within the service sectors. Personal, finance, and business services have seen relatively slow productivity growth but increasing shares of employment, while distributional services experience rapid productivity growth but constant employment shares. The relative prices of education, health services, and personal services are increasing with national income level, while those of communication, financial, accommodation, and food services behave oppositely. Buera and Kaboski (2012) note from the human capital perspective that the contribution to overall economic growth differ substantially according to the share of more educated workers in different service industries. The message delivered is that services differ substantially in the prospect of leading future productivity growth, and more work needs to be done for identifying the sources and implications of such heterogeneity.

There are many areas for future exploration related to the heterogeneity within the service sector. Two worth mentioning are as follows. First, we can look into how the heterogeneity within the service sector is correlated with other observable characteristics, such as production technologies, occupational structure, average hours worked, human capital intensities, and returns to experience. Eckert, Ganapati, and Walsh (2020), for example, study how a subset of service industries, intensive in information and communication technology (ICT), are responsible for the fast growth of US cities by exploiting the decline in ICT capital price and the ease of expanding scale in cities, using micro data of both firms and workers. Second, there is a need to expand the analysis to more developing economies. Since the service sector has also started to take up the majority of employment in many developing countries, such as in China and India (National Bureau of Statistics of China, 2019; Ministry of Statistics and Programme Implementation, 2018), comparing the patterns across different income levels will buy us more insight into the issue. Much of Africa's rapid growth on average has been in the service sector. Whether this will continue, and whether the service sector can pull workers out of subsistence activities, is an important open question.

Another topic not so heavily studied is the effect of international movement of factors of production on structural transformation. Using subnational remittance flow of Malawian immigrants, Dinkelman, Kumchulesi, and Mariotti (2020) find that labour markets receiving more migrant capital have workers, particularly women, moving out of farming into more capital-intensive non-farm service sectors over the next thirty years. High migrant capital areas accumulated more non-farm physical capital and human capital and were wealthier fifteen years after the migration episode. More detailed patterns can be found with household-level data to study how having a family member working abroad affects the occupation choice of the other people in the household. If we are able to track households over time, it becomes possible to evaluate the intergenerational effect on education attainment and occupation choice of the next generation. These questions are particularly relevant for countries with a non-negligible population working overseas and sending back remittance, such as those in Southeastern Asia and the Caribbean.

Relatedly, micro-level evidence on the effect of foreign direct investment or multinational enterprises on structural transformation is becoming easier to observe with the improving availability of firm-level surveys and administrative data on businesses. These data can be used to study how foreign direct investment has facilitated structural transformation directly by creating more jobs in the non-agricultural sector and as a form of technology transfer, and indirectly through spillover effects to the rest of the economy.

As we turn to data-centered suggestions, one utmost need is to collect more panel data that cover long periods of time, especially in developing countries. Figure 1 summarises existing household panel surveys to the best of our knowledge, and it is apparent that the number of years covered by surveys in high-income economies is in general substantially larger than the number for middle- and low-income economies. Some exceptions include the surveys in Indonesia, Thailand, and Kagera, Tanzania, which cover about twenty years of length. As we obtain more and longer panel surveys from developing countries, we will be able to learn more about the realisation of long-run gains from moving out of agriculture, including intergenerational effects. More generally, more panel data sets in developing countries will allow researchers to better study the longer-run effects of development policy on structural transformation, which is inherently a long-run phenomenon.

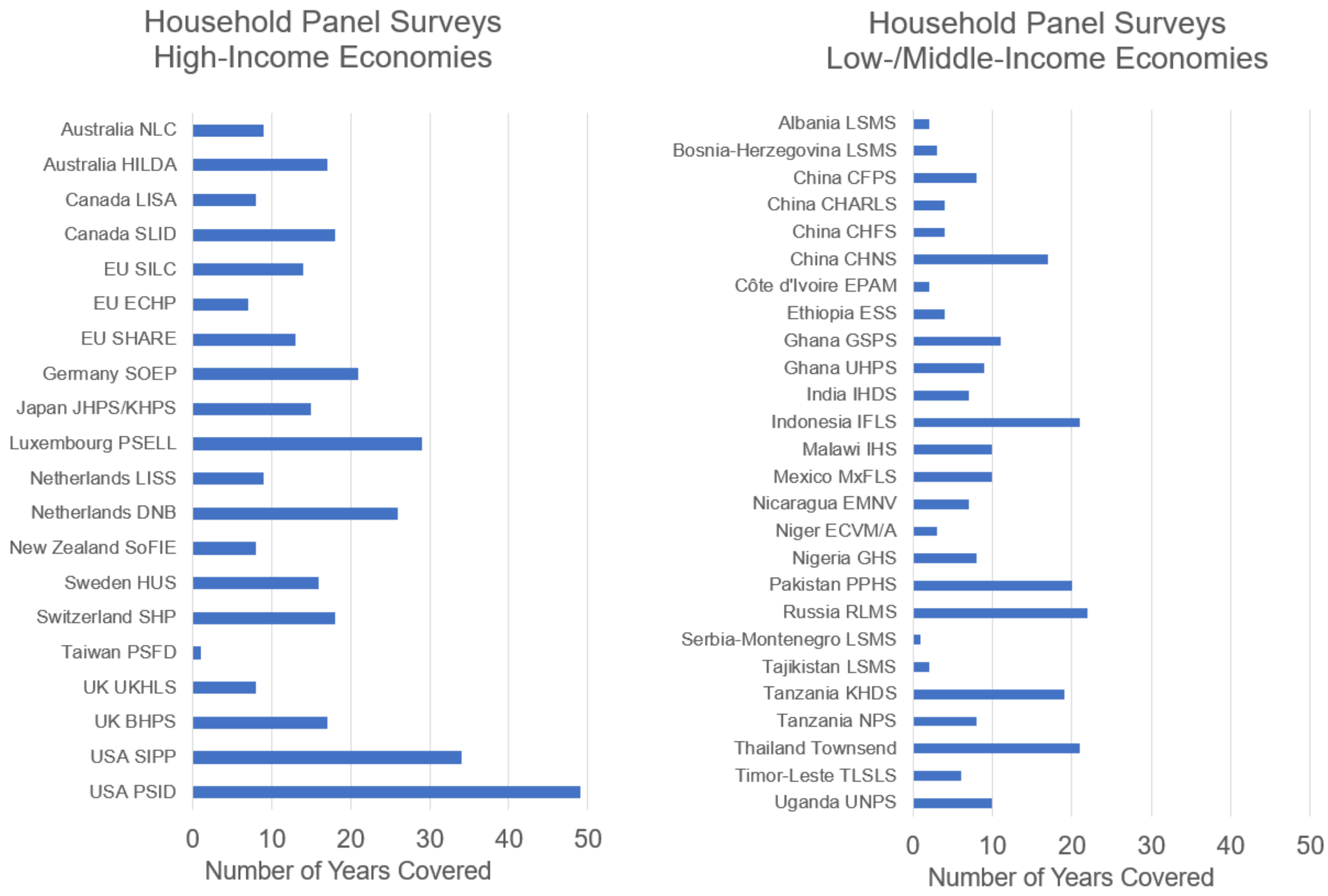


Figure 1: Panel Surveys around the World

*Sources*: Collected by authors.

A promising new longitudinal dataset is the Young Lives project that tracks 12,000 children in four different countries since 2010 when they are still in school. As the older cohort have already entered the workforce, the rich individual history collected for the same person will provide more information about the determinants of career choices and other labour market and family outcomes.

We also call for more effort on the time-use module in household surveys or even independent time-use surveys. Currently available data come almost entirely from developed countries, such as the data set compiled by Ramey and Francis (2009) for the US and those for Japan and European countries accessible from the Centre for Time Use Research. While useful, these data sets can be complemented with input from developing countries, which will allow us to undertake more meaningful comparisons of the structure of time use across development stages. Furthermore, time-use data from developing countries provide invaluable information for assessing welfare not only through the quantity of hours, but also the quality of enjoyment. For example, the 1985 Time Use Survey has a part that asks interviewees to rate their enjoyment of various activities on a scale from zero to ten, the results of which are shown in Table 1. One recent study by Aguiar, Bils, Charles, and Hurst (forthcoming) explains the falling market hours of young cohorts by improved quality of leisure at home, setting an example of how more data on the enjoyment of time use may be used to explore structural differences in the labour market. It is understandable, however, that an average rating may disguise rich variations between people in different occupations, living in rural or urban areas, or with large gaps in income levels, not to mention the difference between people in rich and poor countries.

TABLE 1—ENJOYMENT OF VARIOUS ACTIVITIES IN 1985

| | | | |
|---|---|---|---|
| 9.3 | Sex | 6.9 | |
| 9.2 | Play sports | 6.8 | |
| 9.1 | Fishing | 6.7 | **Second job** |
| 9 | Art, music | 6.6 | **Cook, work at home, shop** |
| 8.9 | Bars, lounges | 6.5 | |
| 8.8 | Play with kids, hug and kiss | 6.4 | **Child care, help adults** |
| 8.7 | | 6.3 | **Work commute** |
| 8.6 | Talk/read to kids | 6.2 | |
| 8.5 | Sleep, church, attend movies | 6.1 | **Dress** |
| 8.4 | | 6 | Pet care, **classes** |
| 8.3 | Read, walk | 5.9 | **Errands** |
| 8.2 | Work break, meals out, visit | 5.8 | **Housework** |
| 8.1 | | 5.7 | |
| 8 | Talk with family | 5.6 | |
| 7.9 | Lunch break | 5.5 | **Home repair, grocery shopping** |
| 7.8 | Meal at home, TV, read paper | 5.4 | |
| 7.7 | Knit, sew | 5.3 | **Homework** |
| 7.6 | | 5.2 | **Pay bills, iron** |
| 7.5 | Recreational trip | 5.1 | |
| 7.4 | | 5 | **Yardwork** |
| 7.3 | Hobbies | 4.9 | **Clean house, dishes** |
| 7.2 | **Baby care**, exercise, meetings | 4.8 | **Laundry** |
| 7.1 | Gardening | 4.7 | **Child health, doctor, dentist** |
| 7 | **Work, homework help, bathe** | 4.6 | **Car repair shop** |

*Notes:* Categories in bold are classified as nonleisure activities. Baby care is included only because most of the time use surveys do not distinguish baby care from other child care. Pet care is classified as a leisure activity because early time use surveys did not include it as household production.
*Source:* Robinson and Godbey (1999), Appendix O, as cited in Ramey and Francis (2006).

The third suggestion on data improvement lies in the measurement of non-agricultural output, especially for informal family businesses and sole proprietorships. The literature has been emphasising the errors in measuring agricultural output (see Herrendorf and Schoellman 2015 and Jerven 2013, among others). In recent years, the development of the Integrated Surveys on Agriculture as part of the LSMS project has greatly improved the way we measure agricultural output. In contrast, the measurement on non-agriculture has lagged behind. For instance, the current modules ask vague questions about the average level of sales in a high month, an average month, and a low month, which naturally involves huge reporting error, let alone intentional misreporting.[11] In addition, we take note that the appropriate questions to ask may differ according to the type of business the interviewee engages in. For example, we want to ask a trader how often the inventory gets refilled, what the average volume of

[11] Indeed, Hurst, Li, and Pugsley (2014) find that self-employed workers underreport their income not only to tax authorities but also to household surveys in the U.S., at a level around 25 percent.

new stock is, and how much sales are for particular types of product in different seasons. For a household mill that processes agricultural product, we would instead ask the sales price of the product, the market value of crops used as raw materials, and the price of any machinery used for processing at the time of purchase and of the survey. The set of questions may differ again when we interview someone with a service occupation. Given the rising importance of non-agricultural activities in the developing world, the marginal value of improving the non-agriculture module in household surveys cannot be over-exaggerated.

One new type of data gradually gaining popularity in this literature is remote sensing data from satellites at micro geographic levels. Donaldson and Storeygard (2016) offer a nice discussion on the current and potential applications of such data. This data has proved useful in measuring the degree of regional development through night lights (e.g. Henderson, Storeygard, and Weil, 2012) and providing information about the quality of land for agricultural production (e.g. Costinot, Donaldson, and Smith, 2016). The popular Global Agro-Ecological Zones data used among agricultural economists, although not collected by satellite, have been organised in the same gridded fashion to ease the usage alongside satellite data. We believe that the merits of these data have just started to be recognised in the research of structural transformation, and expect more fruitful results to come in the near future.

Our last recommendation on data improvement focuses on physical and business capital. One good example of such data is the National Baseline Survey on Micro, Small and Medium Enterprises in Tanzania conducted by their Ministry of Trade and Industry. The survey covers a wide range of metrics on small and medium business and their owners. The interviews include questions that directly ask the owners about the constraints they face and the skills and services they need to facilitate the growth of their businesses.

We end our remark with a discussion on the appropriate use of experimental data when addressing questions about structural transformation. Thanks to the effort of numerous economists, scholars, staff members, and research assistants, among whom Abhijit Banerjee, Esther Duflo, and Michael Kremer gained special recognition, the field of development economics has in no way a shortage of randomised controlled trials (RCTs). The advantage of clear identification makes it easy to draw inference from the experiments and quantify the gains and losses precisely. At the same time, economists often shake their heads at attempts to extrapolate the results from RCTs for policy recommendations, which requires estimates of average treatment effects. Unlike medical trials in which patients are truly assigned treatments at random, RCTs are not capable to force random assignments for both ethical and practical reasons. The best we can do is to identify the effect of being offered the treatment at random or based on some exogenous variations correlated to some instrumental variables, when subjects in the treatment group has the option to take up the treatment while those in the control group do not. Imbens and Angrist (1994) coin the term local average treatment effect (LATE) to describe such effect on the marginal population who accept the treatment. Deaton (2009), Heckman and Urzua (2009), and Imbens (2010) exchanged a round of perspectives on the benefits and limitations of RCTs and natural experiments.

Due to the long-run aggregate nature of structural transformation, experimental results alone are generally not sufficient and need to be complemented with structural models for interpretation in this literature. We give two reasons for this statement. First, there is a need to account for the people who have the chance but choose not to take up the treatment – for example, those who do not migrate in response to a subsidy and those who refuse to take up a loan when offered. Their motivation and their potential reaction to alternative treatment are both economically relevant. Second, we note that model-free inference from the experiments requires no spillover of the treatment effect to the control group, which is often not satisfied in the context of structural transformation due to general equilibrium effect. To illustrate this point, let us consider a rainfall shock that covers exactly half of the cultivated land in a village. As much as we want to infer the effect of precipitation on income by comparing the treatment and control group, the higher yield of the treated households inevitably imposes an income effect to all villagers, including those in the control group, thereby raising the demand for labour and goods produced by the untreated. A structural model is necessary in such cases to help us evaluate the overall effect of the treatment. Buera, Kaboski, and Shin (forthcoming) provide a concrete example of how the impact of microfinance programs differ substantially in terms of partial and general equilibrium effect.

As we encourage the use of structural model in interpreting experiments, it is by no means a rare practice in the structural transformation literature. Kaboski and Townsend (2011), Brooks and Donovan (forthcoming), Baseler (2020), and Lagakos, Mobarak, and Waugh (2020) are several examples, among many others, that apply this method to address important questions in the literature. Of course, structural models are no panacea. But at the very least, they are able to offer a viable path towards more informative policy lessons drawn from the various experiments.

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