Empirical Paper

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The direct employment impact of public investment

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Abstract: We evaluate the direct employment effect of the public investment in key infrastructure – electricity, roads, schools and hospitals, and water and sanitation. Using rich firm-level panel data from 41 countries over 19 years, we estimate that US$1 million of public spending on infrastructure creates 3–7 jobs in advanced economies, 10–17 jobs in emerging market economies, and 16–30 jobs in low-income developing countries. As a comparison, US$1 million in public spending on R&D yields 5–11 jobs in R&D in OECD countries. Green investment and investment with a larger R&D component deliver a higher employment effect. Overall, we estimate that 1% of global GDP in public investment can create more than seven million jobs worldwide through its direct employment effects alone.

Keywords: COVID, employment, public investment, stimulus
JEL Classification: E22, E24, H54

1 Introduction

The global recession triggered by the COVID-19 pandemic has been devastating, particularly for employment. The sharp contraction in economic activity is accompanied by a significant rise in unemployment and underemployment. In 2020, 8.8 percent of global working hours were lost relative to the fourth quarter of 2019, equivalent to 255 million full-time jobs – approximately four times greater than in the global financial crisis (GFC) in 2009 [International Labour Organisation, 2021]. Moreover, the pandemic disproportionately affected low-skilled workers who could not telework and lower-middle-income countries. With the expected recovery from 2021, unemployment rates across advanced and emerging market economies (EMEs) are expected to remain elevated [International Monetary Fund, 2021]. Full-time job losses will remain above 130 million, relative to the fourth quarter of 2019 [International Labour Organisation, 2021]. This persistent weakness in the labor market gives rise to hysteresis effects and could increase the extent of long-term unemployment [Blanchard and Summers, 1986].

Well-designed recovery packages—which include ramped-up spending on public investment—can limit the long-term scarring on the labor market. Public investment spending multipliers are particularly large during recessions [Auerbach and Gorodnichenko, 2013]. Economists have also utilized economic recessions to model and quantify the "job multipliers" of fiscal stimulus spending but with mixed results. For instance, the American Recovery and Reinvestment Act (ARRA) of 2009 is estimated to have yielded about six to eight jobs per US$1 million spent in the short term [Garin, 2019; Ramey, 2020; Wilson, 2012]; conversely, the

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Civilian Conservation Corps operating between 1933 and 1942 in the United States —the archetype of public works—had negligible short-term employment impact [Aizer et al., 2020].[1]

The focus of this paper is on public investment for the post-COVID-19 recovery phase, where social distancing is a nonsignificant factor.[2] Importantly, though, public investment projects are compatible with stricter social distancing conditions. For example, infrastructure design and engineering work is suitable for telework, machine operators are distanced by the nature of their work, and physical construction workers rarely work in close proximity, and use masks and other protective equipment that safeguard against contagion. Despite not being susceptible to remote work, construction employment seems relatively unaffected by the pandemic because of these reasons [Papanikolaou and Schmidt, 2020].

Public infrastructure projects are usually performed through contractors, either state-owned or private (i.e., rarely performed directly by public administrations through their payroll). Every U.S. dollar spent in public investment goes to some company's revenue, subsequently increasing payroll and employment. Construction companies' revenues come from public and private contracts. Construction companies arguably behave similarly in terms of employment efficiency regarding the source of revenue. Hence, estimating the job elasticity to revenue gives a first-order estimation of the direct job creation impact of public investment at the firm level. While reverse causality from employment to revenues is expected to occur in businesses driven by marketing and salesforce efforts (e.g., consumer goods and services), it is less likely in construction companies whose revenues are driven by available contracts and competitive bidding.

Recent research focuses on the general labor impact of public investment [e.g., Bredemeier et al., 2022; Faria-e-Castro, 2021]. Other studies estimate it in specific countries. For example, Alloza and Sanz [2021] use a staggered difference-in-differences approach in Spanish on municipalities and estimate that local investment projects reduced unemployment by 7.4 jobs per EUR 1 million (i.e., 6.4 jobs per US$1 million at the average 2020–2021 exchange rate). Habiyaremye et al. [2021] use a "bucket" method [Batini et al., 2014] and estimate that the South African ZAR 2.3 trillion (US$120 billion) stimulus infrastructure plan contributed to 14.7–18.6 jobs per US$1 million, where 9.8–14.5 jobs per US$1 million are directly attributable to the stimulus program. Nonetheless, there is a lack of global empirical evidence. This paper presents a comprehensive and replicable methodology to quantify the direct employment effect of infrastructure development and maintenance in various key sectors—electricity, roads, schools and hospitals, and water and sanitation—worldwide by country income group. These sectors account for the lion's share of public investment in infrastructure and are on the IMF's focus during the assessment of the additional spending required to meet the United Nations' Sustainable Development Goals (SDGs) by 2030 [Gaspar et al., 2019].

Our results indicate that public spending on infrastructure investments can make a meaningful contribution to job creation. We find that one percentage point of global GDP in additional spending on public investment can create more than seven million jobs worldwide through its direct employment effects alone, i.e., about 5.4% of the full-time equivalent jobs lost in 2021 relative to the fourth quarter of 2019 [International Labour Organisation, 2021]. The total labor impact of 1% of GDP—through direct and indirect macroeconomic effects—is estimated at 20–33 million jobs [International Monetary Fund, 2020b]. In the same vein, US$1 million in public spending on infrastructure can create 3–6.6 jobs in advanced economies (AEs), 10.4–17.2 jobs in EMEs, and 16–30.2 jobs in low-income developing countries (LIDCs). We also find that green investments have a higher employment impact. With these new estimates, the paper

1 Sometimes, the terms "public investment" and "public works" are used interchangeably. The American Public Works Association defines public works as "the combination of physical assets, management practices, policies, and personnel necessary for the government to provide and sustain structures and services essential to the welfare and acceptable quality of life for its citizens" (cf. https://www.apwa.net/MYAPWA/About/What_is_Public_ Works/MyApwa/Apwa_Public/About/What_Is_Public_Works.aspx). I.e., "provide and sustain" mean both development of new and maintenance of existing infrastructure.

2 See Yackovlev et al. [2020] for a classification on how the IMF operationalizes engagement on social spending during and in the aftermath of the COVID-19 crisis.

contributes to the literature by covering a wider spectrum of sectors and countries, and by quantifying the labor multipliers by income groups. Hence, by providing estimates by country income groups, the paper informs the discussion on the employment effects of scaling up public investments.

The remainder of this paper is organized as follows. Section 2 presents the data and methodology. Section 3 presents the results of our analysis. Section 4 discusses welfare and political economy considerations and Section 5 concludes with policy recommendations.

2 Data and methodology

We assemble a rich panel dataset of construction companies involved in the design, planning, building, and maintenance of projects in social (health and education) and physical infrastructure (roads, electricity, and water and sanitation) based on Compustat and Orbis. These two sources primarily cover companies—both private and state-owned—that are not publicly listed worldwide. Companies are filtered by using industry codes (see Table 1).[3] The industry codes for electricity, roads, and water and sanitation are precisely defined. For schools and hospitals, we use a residual industry code for the construction of institutional buildings that excludes housing and industrial sites.[4]

We match the span of both datasets from 1999 to 2017 and adjust revenue values to constant 2015 U.S. dollars using GDP deflators. We then drop outliers by revenue and employment and retain companies with at least five annual observations to have sufficient within-company variation for fixed effects and clustering [Kézdi, 2004; Wooldridge, 2003] and to avoid biasing our estimates with *cyclical* shell companies.[5] Limited data granularity does not allow us to disentangle labor utilization in new investment versus maintenance, part-time versus full-time, skilled versus unskilled labor, and imported versus local labor.

Table 1. Sectors and industries by data source

Sector	Compustat (NAICS)	Orbis (CPA)
Electricity	**237130** – Power and Communication Line and Related Structures Construction	**F42.2.1** – Construction of utility projects for fluids **F42.2.2** – Construction of utility projects for electricity and telecommunications
Roads	**237310** – Highway, Street, and Bridge Construction **333120** – Construction Machinery Manufacturing (Drags, road construction and road maintenance equipment, manufacturing)	**F42.1** – Construction of roads and railways, including: **F42.1.1** – Construction of roads and motorways **F42.1.2** – Construction of railways and underground railways **F42.1.3** – Construction of bridges and tunnels
Schools and hospitals	**2362** – Commercial and Institutional Building Construction	**F42.9.9** – Construction of other civil engineering projects n.e.c.
Water and sanitation	**237110** – Water and Sewer Line and Related Structures Construction	**F42.9.1** – Construction of water projects

Note: NAICS is the North American Industry Classification System (cf. https://www.census.gov/eos/www/naics/) and CPA is the European Classification of Products by Activity (cf. https://ec.europa.eu/eurostat/web/cpa).
Source: Compustat and Orbis.

3 Previous work using this dataset include Baum et al. [2019].

4 There are no exclusive industrial codes for construction companies in education and health, i.e., the classification codes contain not only schools and hospitals, but also the construction of government administrative buildings, prisons, colleges, museums, sports facilities, etc.

5 Cyclical shell companies are corporate vehicles that appear during boom and disappear during bust periods. Also, data from companies with single or a few observations is likely to be less reliable.

Table 2. Summary statistics

Advanced economies	**Countries**	**Obs.**	**Mean**	**Std. Dev.**
Revenue	27	43,485	11.0	14.5
Employees	27	43,485	45.1	74.4
Emerging market economies	**Countries**	**Obs.**	**Mean**	**Std. Dev.**
Revenue	14	4,095	7.7	11.8
Employees	14	4,095	123.4	195.0

Notes: The summary statistics present revenues in millions of 2015 U.S. dollars and employment by income group. The sample data is for 1999–2017 and covers firms with at least five annual observations.
Source: Author's calculations based on Compustat and Orbis.

The resulting dataset comprises 43,485 observations for 5,123 firms in 27 AEs and 4,095 observations for 556 firms in 14 EMEs.[6] There are no data from LIDCs. Table 2 presents the summary statistics of revenues and the number of employees for AEs and EMEs.

The observations are relatively well spread across the electricity, roads, and schools and hospital sectors (between 12 and 19 thousand observations in each), with fewer observations in the water and sanitation sector (about 1,500 observations). Despite its richness, the resulting dataset should be treated as illustrative rather than statistically representative: most of the sampled companies are medium-sized and unlisted and with several years of audited financial statements.

We compute the marginal pass-through from spending on public investment to employment by regressing employment on revenues by sector and country income group at the individual firm level.[7] We estimate the following regression:

$$L_{i,t} = \alpha + \beta_s \left[R_{i,t} \times S_i \right] + X + \varepsilon \tag{1}$$

where $L_{i,t}$ and $R_{i,t}$ are the employment and revenue in firm i at time t, S_i is the vector of sector dummy variables, and X is the country (Model 1) or firm (Models 2–4) fixed effects. All regressions are clustered at the firm level. The point estimates of β_s represent the change in employment per additional unit of revenue (in our case, US$1 million of 2015) per sector.

The estimation in Eq. (1) is tinted by an important caveat. The aim of public investment is not job creation but public goods creation, i.e., labor is an input variable into the production function of public goods, along with capital and institutions. In the process of public goods creation, the reduced-form job creation estimation assumes that there are two inefficiencies: (i) low productivity at the public administration level that generates losses from the budget to contractors, due to purely designed, selected, and executed project but also due to red tape and corruption, and (ii) low productivity at the contractor level, i.e., job creation may not translate into public goods creation. These two inefficiencies are arguably interrelated: corruption increases public investment but reduces its productivity [Tanzi and Davoodi, 1998]. These effects are absorbed by the country and firm fixed effects in the regressions. A detailed analysis of the impact of corruption on public investment employment is beyond the scope of this paper.

6 The sample of AEs includes: Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Italy, Japan, Korea, Latvia, Lithuania, Luxemburg, the Netherlands, Portugal, Singapore, Slovakia, Slovenia, Spain, Sweden, Taiwan Province of China, United Kingdom, and United States; the sample of EMEs includes: Bosnia and Herzegovina, Bulgaria, China, Croatia, Hungary, Indonesia, Kazakhstan, North Macedonia, Malaysia, Poland, Romania, Serbia, South Africa, and Ukraine.

7 The straightforward average employment per unit of public expenditure or firm revenue would upwardly bias our estimations since it would include overhead employees.

3 Results

Table 3 presents the results of the regressions. Model 1 uses pool data with country-fixed effects, thus assuming that labor moves freely across companies within countries. Model 2 uses firm-level fixed effects, which implies that labor stickiness at the firm level.[8]

The GFC, which originated in the housing sector, hit the construction business severely; therefore, including these years could bias our estimates. Also, the elasticities of hiring and firing could be asymmetrical. For robustness, Model 3 restricts the estimations to the years 1999–2007 and 2010–2017 – i.e., without taking into account the GFC. The labor market effects induced by the GFC do not overlap in time in all countries. Thus, Model 4 computes only the one-sided job elasticity to revenue increases. The results are similar to the estimations of Model 2 and show that the job elasticity to revenues is not cycle-dependent.

The coefficients have the expected sign and are predominantly statistically significant. Regression results show that the employment impact is inversely correlated to a country's income level. The construction of hospitals and schools is comparatively less labor-intensive in AEs which points out to higher standardization and investment in equipment rather than in utilizing labor.

A large component of firms' cost of goods sold (COGS) is equipment, materials, and subcontracted work. Part of the marginal increase in the primary contractor's revenues increases employment and part increases the demand from sectoral suppliers and subcontractors, which subsequently increases employment. The sector-wise direct job creation depends on the levels of labor intensity. For example, an intensity of two jobs per million U.S. dollars invested in water and sanitation and a 50% pass-through to the supply chain means that for each US$1 million, the main contractor hires two employees and spends US$500 thousand in equipment, materials, and subcontractors; these companies hire one employee and spend US$250 thousand in equipment, materials, and subcontractors, and so on. Thus, the total sectoral job creation per million U.S. dollars is the sum of the geometric series given by Equation (2):

$$Jobs_s = \beta_s + \lambda\beta_s + \lambda^2\beta_s + \ldots = \frac{\beta_s}{1-\lambda} \tag{2}$$

where $Jobs_s$ is the total direct jobs created per US$1 million invested in sector s, β_s is the estimate from Eq. (1) and reported in Table 3,[9] and $\lambda \in (0,1)$ is the labor intensity path-through share to the supply chain in the sector. In line with empirical evidence from construction companies,[10] we assume supply chain pass-through between 35% (low) and 65% (high), with a midpoint of 50%.

Table 4 and Figure 1 summarize the main results for high, medium, and low labor mobility in employment within firms and sectors and different levels of labor intensity. The labor impact in LIDCs is computed as a linear extrapolation from AEs and EMEs.[11]

The employment impact for intermediate levels of labor mobility and labor intensity ranges from 3 jobs in the schools and hospitals to 6.6 jobs in electricity per million U.S. dollars of spending in AEs and from 16

8 The link between firm-level fixed effects and labor mobility follows an *a-contrario* heuristics: whereas Model 2 estimates the average within-firm job creation elasticity, by removing the firm-level fixed effect. Model 1 estimates the between-firm covariance of revenues and jobs, thus allowing for within-sector labor mobility [Mummolo and Peterson, 2018].

9 The job content coefficient β_s may not be the same for the different layers of contracting. Since we cannot disaggregate upstream and downstream construction companies by industrial code, the estimations in Table 3 reflect the average job content by sector at all levels of contracting.

10 Cf. the range of the sum of materials, equipment, and subcontracting costs to revenue in the 10-K statements of construction companies. The share of pass-through can be estimated as COGS to Revenue, minus the direct labor cost within construction companies ranging between 10 and 30 percent. For example, at a gross profit of 15 percent (COGS/Revenue = 85%) and a direct labor cost of 20 percent of revenue, the pass-through is 65 percent. See, for example, Emrath [2015].

11 The lack of financial data for companies in LIDC is amended with a linear extrapolation. Linear extrapolation creates a tangent line from the point estimates of AEs to EMEs, extending it beyond EMEs, and provides a fair approximation since it extends the graph not far beyond the known data for EMEs.

Table 3. Immediate Job Content in Selected Infrastructure Sectors

Advanced economies	**(1)**	**(2)**	**(3)**	**(4)**
	Pool	**Panel**	**Without 2008–2009**	**Revenue increases**
Electricity	4.278***	2.363***	2.390***	2.433***
	(0.238)	(0.206)	(0.217)	(0.210)
Roads	3.124***	1.722***	1.742***	1.817***
	(0.114)	(0.128)	(0.141)	(0.142)
Schools and hospitals	2.223***	0.850***	0.817***	0.824***
	(0.238)	(0.125)	(0.116)	(0.166)
Water and sanitation	2.778***	1.206***	1.184***	1.153***
	(0.348)	(0.235)	(0.252)	(0.290)
Fixed effects	Country	Firm	Firm	Firm
Clustered at	Firm	Firm	Firm	Firm
Observations	43,485	43,485	38,971	27,244
R-squared	0.637	0.201	0.198	0.203
Number of clusters	5,123	5,123	5,123	5,123
Emerging market economies	**(1)**	**(2)**	**(3)**	**(4)**
	Pool	**Panel**	**Without 2008–2009**	**Revenue increases**
Electricity	8.120***	7.406**	8.300**	7.832**
	(1.743)	(3.175)	(3.449)	(3.740)
Roads	8.178***	2.287***	2.037***	1.902**
	(1.370)	(0.679)	(0.722)	(0.779)
Schools and hospitals	7.764***	4.578**	4.777**	3.898**
	(2.376)	(1.788)	(2.171)	(1.663)
Water and sanitation	12.28***	4.965*	5.587*	4.829
	(4.318)	(2.593)	(2.973)	(4.011)
Fixed effects	Country	Firm	Firm	Firm
Clustered at	Firm	Firm	Firm	Firm
Observations	4,095	4,095	3,660	2,539
R-squared	0.563	0.157	0.168	0.161
Number of clusters	556	556	556	556

Notes: This table presents the results of regressions of employment on revenues in millions of 2015 U.S. dollars. Model 1 assumes that labor moves freely across companies within sectors, while Models 2–4 assume that labor stays at the firm level. For robustness, Model 3 restricts the estimations to the years 1999–2007 and 2010–2017, i.e., without the Global Financial Crisis years of 2008–2009 and Model 4 computes the impact on employment of revenue increases only. The sample data is from 1999 to 2017, and only firms with at least five annual observations were kept. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parenthesis.

*, **, and *** denote significance at 10, 5, and 1%, respectively.

Source: Author's own estimations based on Compustat and Orbis.

jobs in roads to 30.4 jobs in water and sanitation in LIDCs. This means each unit of public spending creates more direct jobs in electricity in high-income countries and more jobs in water and sanitation in low-income countries.

Sustainable "green" investment could create more jobs than traditional investment [Allan et al., 2020; Coalition of Finance Ministers for Climate Action, 2020; Garrett-Peltier, 2017; International Monetary Fund,

Table 4. Job content by sectors and income group

Advanced economies		**Labor mobility**		
	Labor intensity	**High**	**Medium**	**Low**
Energy	High	12.2	9.4	6.8
	Medium	8.6	6.6	4.7
	Low	6.6	5.1	3.6
Roads	High	8.9	6.9	4.9
	Medium	6.2	4.8	3.4
	Low	4.8	3.7	2.6
Schools and hospitals	High	6.4	4.3	2.4
	Medium	4.4	3.0	1.7
	Low	3.4	2.3	1.3
Water and sanitation	High	7.9	5.7	3.4
	Medium	5.6	4.0	2.4
	Low	4.3	3.1	1.9
Emerging market economies		**Labor mobility**		
	Labor intensity	**High**	**Medium**	**Low**
Energy	High	23.2	22.3	21.2
	Medium	16.2	15.6	14.8
	Low	12.5	12.0	11.4
Roads	High	23.4	14.9	6.5
	Medium	16.4	10.4	4.6
	Low	12.6	8.0	3.5
Schools and hospitals	High	22.2	17.7	13.1
	Medium	15.5	12.4	9.2
	Low	11.9	9.5	7.0
Water and sanitation	High	35.1	24.6	14.2
	Medium	24.6	17.2	9.9
	Low	18.9	13.2	7.6
Low-income developing countries		**Labor mobility**		
	Labor intensity	**High**	**Medium**	**Low**
Energy	High	37.9	35.1	32.5
	Medium	26.6	24.6	22.7
	Low	20.4	18.9	17.5
Roads	High	31.4	22.9	14.5
	Medium	22.0	16.0	10.2
	Low	16.9	12.3	7.8
Schools and hospitals	High	35.6	31.1	26.5
	Medium	24.9	21.8	18.6
	Low	19.2	16.8	14.3
Water and sanitation	High	53.9	43.4	33.0
	Medium	37.8	30.4	23.1
	Low	29.0	23.4	17.8

Notes: This table presents the estimates of direct job impact per US$1 million spent in public investment by sector, income level, and labor-market characteristics. Labor mobility is the easiness of moving across companies within sectors (given by the point estimates in Table 3) and labor intensity is the path-through share to the supply chain in the sector (parametrized between 35% and 65%). The coefficients for LIDC are computed as a linear extrapolation from AE and EME. The sample data is for 1999–2017.

Source: Author's own estimations based on Compustat and Orbis.

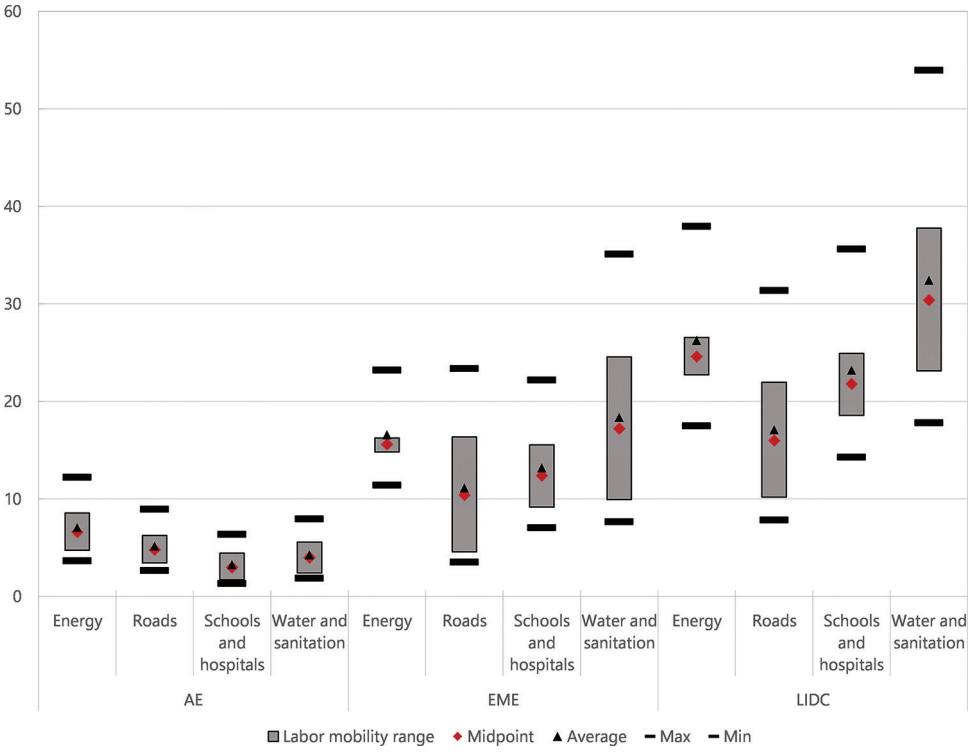


Figure 1. Job Content per US$1 Million of additional investment.

Notes: The figure shows the estimates of the job content of US$1 million of investment for different sectors and country groups based on regressions of employment on revenues in 1999–2017, covering 47,580 observations for 5,679 privately owned and state-owned enterprises. The stripped bar and the red rhombus represent the labor mobility range and midpoint estimate, respectively, for medium labor intensity. Labor mobility is the easiness of moving across companies within sectors (given by the point estimates in Table 3) and labor intensity is the path-through share to the supply chain in the sector (parametrized between 35% and 65%). The thick horizontal dashes and the black triangle represent the overall maximum and minimum values and the average estimates, respectively, accounting for wide ranges of labor intensity. The estimates for low-income countries are extrapolated from the other estimates.

AE: advanced economies; EME: emerging market economies; LIDC: low-income developing economies.

Source: Author's own estimations based on Compustat and Orbis.

2019; O'Callaghan et al., 2022]. Policymakers and scholars have advocated for a green recovery in the wake of the GFC [Houser et al., 2009; Jacobs, 2012]. The Great Lockdown is calling once again for similar measures [Allan et al., 2020; Coalition of Finance Ministers for Climate Action, 2020]. Jobs created in the renewable energy sector include solar panel installation and building retrofitting, which have a high component of local labor. In addition, many jobs in renewables do not require high educational attainment and have low barriers to entry. In the United States, less than 20% of workers in clean-energy production and energy-efficient occupations have college degrees [Muro et al., 2019]. According to the literature, job intensity – net of job losses in traditional industries – is estimated at 5–10 jobs per US$1 million invested in green electricity, 2.4–12.5 jobs in efficient new buildings like schools and hospitals, and 5.7–14 in green water and sanitation through efficient agricultural pumps and recycling [Popp et al., 2020; International Energy Agency, 2020]. Altogether, the job creation multipliers per US$1 million of green investment is similar to the estimates of high labor intensity reported in Table 4.

To complement our analysis and for additional robustness of our estimates, we compute the impact of public spending on R&D on employment in R&D by type of recipient, using a similar approach of computing the employment elasticity to additional revenues. R&D is a smaller component of public investment, which goes primarily to government institutions and higher education, and unlike other types of investment, employs only high-skilled labor. These are higher-quality jobs and are expected to increase, particularly in

Table 5. Job content in R&D by recipient type

	(1)	(2)	(3)	(4)
	Government	**Higher education**	**Business**	**Non-profit**
Spending in R&D (US$ million)	4.837***	10.99***	10.55**	4.477**
	(1.281)	(3.970)	(4.609)	(2.020)
Country fixed effects	Yes	Yes	Yes	Yes
Cluster at country level	Yes	Yes	Yes	Yes
Observations	409	405	414	287
R-squared	0.690	0.425	0.635	0.331
Number of clusters	36	36	37	25

Notes: This table presents the results of panel regressions of employment on spending in R&D in millions of 2015 U.S. dollars in OECD countries. The models correspond to recipients of R&D financing: government, higher education, business, and private non-profit. The sample data is for 1999–2015. Heteroskedasticity-robust standard errors clustered at the country level are reported in parenthesis.

*, **, and *** denote significance at 10, 5, and 1%, respectively.

Source: Author's calculations.

the health sector. Spending on R&D is essential for long-term sustainable growth. We use OECD country-level data on R&D disaggregated by recipient type and compute the pass-through from R&D spending to employment in R&D. Overall, we collect 587 observations from 40 countries between 1999 and 2015 (with gaps).[12] We convert spending in terms of annual shares of GDP to constant 2015 U.S. dollars and run panel regressions analogous to those for public investment. Table 5 reports the results of the regressions regarding R&D spending by recipient type in OECD countries. The point estimates in Table 3 and Table 5 are in the same order of magnitude in terms of jobs created by US$1 million, which validates the approach.

Government R&D generates an estimated 4.8 jobs in R&D per US$1 million invested. Higher education R&D is nearly two times higher, possibly because it focuses on fundamental research and requires less capital than government R&D, which in turn focuses often on capital-intensive experimental and military applications [Chapter 8 in Organization for Economic Cooperation and Development, 2015].[13] However, spending on higher education R&D only accounts on average for 0.36% of GDP (about 20% of total R&D spending) and the government R&D for 0.22% of GDP (about 13% of total R&D spending). The largest R&D spending was carried by business for a total of 1.1% of GDP and 61% of total spending in R&D.

Basic R&D is long-term and is primarily financed by the public sector, while the private sector finances are mainly applied R&D, which is medium-term at best. The job content of green R&D is estimated at 3–8 jobs per US$1 million of investment [International Energy Agency, 2020]; i.e., green R&D is not more costly than conventional R&D and can have a lasting long-term impact.

Data limitations prevent us from getting a clear picture of the labor impact at different wage levels, full versus part-time jobs, and types and degrees of green investment. The elasticity of job creation to wages is estimated at the income level group. To the extent that these dimensions are country- and firm-specific and they are absorbed by the fixed effects.

4 Welfare and political economy considerations

Public investment alternatives are interlinked with institutional capacity and fiscal space. While AEs have the human and physical capital needed and can borrow at record-low interest rates to scale up public

12 We exclude the blurry "intramural" category, which includes all expenditures for R&D performed within a statistical unit or sector of the economy during a specific period, whatever the source of funds.

13 See, also, Sargent Jr. [2020].

investment, most EMEs and LIDCs find themselves in a much less favorable situation. In these countries, public debt levels are significantly elevated, and the costs of borrowing are much higher. Moreover, in EMEs and LIDCs public investment policies are subject to significant political economy and capacity constraints and tradeoffs. We can identify three relevant areas for the debate on public investment in infrastructure.

State-own enterprises (SOEs), which often undertake public investment projects, have on average higher job intensity than private firms [International Monetary Fund, 2020a]. SOEs operate virtually in every country, most commonly in sectors such as public utilities, energy, transportation, and banking. In OECD countries, SOEs represent, on average, 4.7% of the labor force, compared to 15.8% by the general government [Ball and Beauvallet, 2013]. In some OECD countries, SOEs employ particularly large parts of the nonagricultural workforce: e.g., Norway 9.6%, Latvia 6.7%, Estonia 4.8%, Hungary 4.2%, France 3.5%, Finland 3.5%, the Czech Republic 3.4%, the Slovak Republic 3.1%, and Italy 3.1% [Organization for Economic Cooperation and Development, 2017]. Job intensity for SOEs is found to be 30% higher compared to private counterparts [Baum et al., 2019]. Possible reasons for this finding are that SOEs tend to be larger and have an implicit employment remit. This result is especially important in EMEs and LIDCs, where SOEs account for more than half of all infrastructure project commitments [International Monetary Fund, 2020a] and often employ large parts of the workforce.

Public-private initiatives are not a panacea when the fiscal space to undertake public investments is limited. First, public-private partnerships are not "free money" from the private sector to ease public-sector financing. The private sector has a pecking order of projects for investment which is driven by profitability and enforcement of property rights. Second, fiscal capacity tends to be correlated with state capacity [Besley and Persson, 2010; Moszoro et al., 2015]. The public and private sectors are complementary in infrastructure when the state has capacity to provide effective regulation and safeguard property rights [Besley and Persson, 2009]. Third, if there is sufficient fiscal space and state capacity, the private sector can contribute (in particular cases) with superior technology and efficient management [Moszoro, 2018]; if there is no fiscal space, the private sector is also likely to be constrained in that jurisdiction, and it is unlikely that the external private capital will solve institutional and financing deficiencies.

Policies on greening the recovery ought to be carefully designed to avoid backlash [Barbier, 2010]. Clean-energy infrastructure has been found to be labor intensive in the short term [Garrett-Peltier, 2017], although not all green investments create jobs quickly [Popp et al., 2020]. Green stimulus/recovery, while yielding more long-term climate benefits, is likely to generate a slower and smaller recovery in jobs and activity than a traditional macroeconomic stimulus [Brahmbhatt, 2021]. Moreover, some forms of green investment are also not job rich in the long term and require specific skills: for example, windmills are capital-intensive and produced in only a few countries. Whereas green investment offers clear global welfare gains (Hicks-Kaldor efficiency), the distributional effects and Pareto efficiency for low-income countries are debatable.

5 Discussion and Conclusions

This paper makes the case that public investment can also support employment in addition to its primary goal of creating infrastructure. The emphasis on job creation is particularly relevant during these unprecedented times that have had a dramatic impact on labor markets. We present an innovative approach to measure the employment impact of public investment, which is carried through sector-specific construction companies. We compute the employment effect of US$1 million of spending by sector and country income group using a rich panel dataset with firm-level data of construction companies from 1999 to 2017. Extrapolating our results to all AEs and EMEs suggests that an increase in public investment equivalent to 1% of GDP could directly create more than seven million jobs in AEs and EMEs through its direct employment effects alone (i.e., about 5.4% of the full-time equivalent jobs lost in 2021 relative to the fourth quarter of 2019; International Labour Organisation, 2021, January). This number is obtained by applying: (i) a job content of 4.9 per US$1 million invested for AEs (unweighted average) to an increase in investment worth 1% of GDP in AEs (ca. US$500 billion in

2020; cf. Appendix 1) and (ii) a job content of 14.8 per US$1 million for emerging markets (similarly to AEs) to 1% of the GDP of EMEs (ca. US$320 billion). The impact could be higher for green investment and investments in R&D with a higher labor intensity.

a) These numbers may underestimate job creation of public investment because of several factors that go beyond the scope of the data, including:
b) Firms with less than five observations are excluded. Thus, the analysis misses the employment increase in *cyclical* companies that are formed during fiscal expansion and disappear in times of fiscal consolidation, and which likely have higher elasticity between revenue and employment.
c) The effects in LIDCs of additional employment are linearly extrapolated from AEs and EMEs. This relationship may arguably be convex: i.e., the impact on employment is likely to increase exponentially the lower the country's income per capita, as infrastructure development is more labor-intensive and the labor force is less specialized, and thus more fungible, in LIDCs [Tanzi, 2019], which means the employment impact imputed for LIDCs by extrapolation is underestimated.
d) The indirect labor impact and spillovers (including Keynesian multiplier effects into other sectors of the economy) are not included. The International Monetary Fund [2020b] estimates that a 1% of GDP increase in public investment in AEs and EMEs has the potential to create, directly and indirectly, between 20 and 33 million jobs.
e) These estimates are pooled and do not distinguish between new projects and maintenance, or between skilled and unskilled labor. *Ceteris paribus*, maintenance projects and projects with a higher unskilled labor component would create more jobs than estimated here.

On the other hand, the job creation estimates may be overstated by the degree of waste from budget allocations to actual contracted public investment. The Public Investment Management Assessment (PIMA) database—which currently covers a cross-section of over 60 countries; see International Monetary Fund [2015], International Monetary Fund [2018]; and IMF's web page on PIMA[14]—can serve as a tentative first approach to correct for this upward bias.

Policies that provide preference for particular sectors in the short term may have longer-term implications. For example, a preference for public works on roads may prevent investment in electricity which is necessary for digital infrastructure. The estimates presented in Table 4 can serve as a tool for policymakers to assess the employment impact and trade-offs of alternative uses of fiscal space between short-term current and long-term capital spending, and between social and physical capital sectors. They also quantify the enhancing employment impact of higher labor mobility (e.g., through training and flexible arrangements) and higher labor content (e.g., in infrastructure maintenance and green investment).

Future works of this type should include the quantification of employment impact by country, in digital infrastructure, and—inasmuch as the industrial classification evolves to encompass this distinction—by green versus brown investment.

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14 Cf. https://infrastructuregovern.imf.org/content/PIMA/Home/PimaTool/What-is-PIMA.html (accessed February 2021).

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Appendix 1. Employment and GDP in Advanced Economies (AEs) and Emerging Market Economies (EMEs)

This appendix contains the list of countries (classified by level of income), the employment in millions of employees, and the GDP in billions of U.S. dollars. The sample includes firm-level data from 38 AEs and 63 EMEs, for a total of 101 economies representing 95% of the global GDP.

Country	Income level	Employment (millions)	GDP (US$ billions)
Albania	Emerging Market Economy	1.1	15.4
Algeria	Emerging Market Economy	11.1	172.8
Argentina	Emerging Market Economy	17.1	445.5
Armenia	Emerging Market Economy	1.6	13.4
Azerbaijan	Emerging Market Economy	5.0	47.2
The Bahamas	Emerging Market Economy	0.2	12.7
Bahrain	Emerging Market Economy	0.9	38.2
Barbados	Emerging Market Economy	0.1	5.2
Belarus	Emerging Market Economy	4.3	62.6
Belize	Emerging Market Economy	0.2	2.0
Bolivia	Emerging Market Economy	5.6	42.4
Bosnia and Herzegovina	Emerging Market Economy	1.0	20.1
Botswana	Emerging Market Economy	1.5	18.7
Brazil	Emerging Market Economy	92.1	1,847.0
Brunei Darussalam	Emerging Market Economy	0.2	12.5
Bulgaria	Emerging Market Economy	3.1	66.2
Cabo Verde	Emerging Market Economy	0.3	2.0
Chile	Emerging Market Economy	8.6	294.2
China	Emerging Market Economy	775.3	1,4140.2
Colombia	Emerging Market Economy	22.9	327.9
Costa Rica	Emerging Market Economy	2.3	61.0
Croatia	Emerging Market Economy	1.4	60.7
Dominican Republic	Emerging Market Economy	4.6	89.5
Ecuador	Emerging Market Economy	7.5	107.9
Egypt	Emerging Market Economy	25.9	302.3
El Salvador	Emerging Market Economy	2.8	26.9
Hungary	Emerging Market Economy	4.5	170.4
India	Emerging Market Economy	32.0	2,935.6
Indonesia	Emerging Market Economy	127.1	1,111.7
Iran	Emerging Market Economy	25.1	458.5
Jamaica	Emerging Market Economy	1.2	15.7
Jordan	Emerging Market Economy	1.8	44.2
Kazakhstan	Emerging Market Economy	8.9	170.3
Kuwait	Emerging Market Economy	2.7	137.6
Malaysia	Emerging Market Economy	15.0	365.3
Mauritius	Emerging Market Economy	0.5	14.4
Mexico	Emerging Market Economy	54.4	1,274.2
Mongolia	Emerging Market Economy	1.3	13.6
Morocco	Emerging Market Economy	11.2	119.0

Continued

Appendix 1. Continued

Country	Income level	Employment (millions)	GDP (US$ billions)
North Macedonia	Emerging Market Economy	0.8	12.7
Oman	Emerging Market Economy	2.3	76.6
Pakistan	Emerging Market Economy	59.8	284.2
Panama	Emerging Market Economy	1.9	68.5
Peru	Emerging Market Economy	16.9	229.0
Philippines	Emerging Market Economy	42.1	356.8
Poland	Emerging Market Economy	16.5	565.9
Qatar	Emerging Market Economy	2.2	191.8
Romania	Emerging Market Economy	8.8	243.7
Russia	Emerging Market Economy	72.7	1,637.9
Serbia	Emerging Market Economy	2.3	51.5
Seychelles	Emerging Market Economy	0.0	1.6
South Africa	Emerging Market Economy	16.6	358.8
Suriname	Emerging Market Economy	0.1	3.8
Thailand	Emerging Market Economy	37.4	529.2
Trinidad and Tobago	Emerging Market Economy	0.6	22.6
Tunisia	Emerging Market Economy	3.5	38.7
Turkey	Emerging Market Economy	28.2	743.7
Turkmenistan	Emerging Market Economy	2.5	46.7
Ukraine	Emerging Market Economy	16.4	150.4
United Arab Emirates	Emerging Market Economy	7.7	405.8
Uruguay	Emerging Market Economy	1.7	59.9
Venezuela	Emerging Market Economy	8.4	70.1
Vietnam	Emerging Market Economy	58.3	261.6
Australia	Advanced Economy	12.9	1,376.3
Austria	Advanced Economy	4.4	447.7
Belgium	Advanced Economy	4.9	517.6
Canada	Advanced Economy	19.0	1,730.9
Cyprus	Advanced Economy	0.4	24.3
Czech Republic	Advanced Economy	5.3	247.0
Denmark	Advanced Economy	2.9	347.2
Estonia	Advanced Economy	0.7	31.0
Finland	Advanced Economy	2.6	269.7
France	Advanced Economy	25.6	2,707.1
Germany	Advanced Economy	42.0	3,863.3
Greece	Advanced Economy	3.9	214.0
Hong Kong SAR	Advanced Economy	3.9	373.0
Iceland	Advanced Economy	0.2	23.9
Ireland	Advanced Economy	2.3	384.9
Israel	Advanced Economy	4.0	387.7
Italy	Advanced Economy	23.3	1,988.6
Japan	Advanced Economy	67.4	5,154.5
Korea	Advanced Economy	26.9	1,629.5

Continued

Appendix 1. Continued

Country	Income level	Employment (millions)	GDP (US$ billions)
Latvia	Advanced Economy	0.9	35.0
Lithuania	Advanced Economy	1.4	53.6
Luxembourg	Advanced Economy	0.5	69.5
Macao SAR	Advanced Economy	0.4	55.1
Malta	Advanced Economy	0.2	14.9
Netherlands	Advanced Economy	8.9	902.4
New Zealand	Advanced Economy	2.7	204.7
Norway	Advanced Economy	2.7	417.6
Portugal	Advanced Economy	5.0	236.4
Puerto Rico	Advanced Economy	1.0	99.9
Singapore	Advanced Economy	3.7	362.8
Slovak Republic	Advanced Economy	2.4	106.6
Slovenia	Advanced Economy	1.0	54.2
Spain	Advanced Economy	19.8	1,397.9
Sweden	Advanced Economy	5.1	528.9
Switzerland	Advanced Economy	5.0	715.4
Taiwan Province of China	Advanced Economy	11.5	586.1
United Kingdom	Advanced Economy	32.8	2,743.6
United States	Advanced Economy	156.9	21,439.5
Sum		2,204.4	83,218.7

Source: WEO and IMF.