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Work in Progress: Improving Youth Labor Market Outcomes in Emerging Market and Developing Economies

Technical Appendices for SDN/19/02

JaeBin Ahn, Zidong An, John Bluedorn, Gabriele Ciminelli, Zsóka Kóczán, Davide Malacrino, Daniela Muhaj, and Patricia Neidlinger

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Prepared by JaeBin Ahn, Zidong An, John Bluedorn, Gabriele Ciminelli, Zsóka Kóczán, Davide Malacrino, Daniela Muhaj, and Patricia Neidlinger[1]

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ECONOMY SAMPLES, VARIABLE DEFINITIONS, DATA SOURCES, AND FURTHER STYLIZED FACTS[1]

A. Samples and Classification of Economies

Each component of the analyses uses the largest available sample of economies with data on labor market indicators and structural variables. In general, the coverage is unbalanced across countries—not all years are available for all countries. It is important to recognize that differences in sample coverage by variable across countries and over time mean that the "average" EMDE for one variable (as captured by its median value within the country group) may not be the "average" EMDE for another variable. This may complicate the interpretation of any comovement of average EMDE behavior across variables. Moreover, the samples used vary with the type of analysis undertaken. See Table 1.1. for details on the country coverage in each analytical sample.

The main economy classification comes from the IMF October 2017 *World Economic Outlook* (WEO), where countries are placed into one of two groups: Advanced Economies (AE) or Emerging Market and Developing Economies (EMDE). The EMDE group may be further split, into those which are low-income developing countries (LIDCs) and those which are not. The geographic/regional classification comes from the World Bank and consists of seven groups: East Asia and Pacific, Europe and Central Asia, Latin America and Caribbean, Middle East and North Africa, North America, South Asia, and sub-Saharan Africa. See again Table 1.1 for the economy and regional groups to which each country belongs.

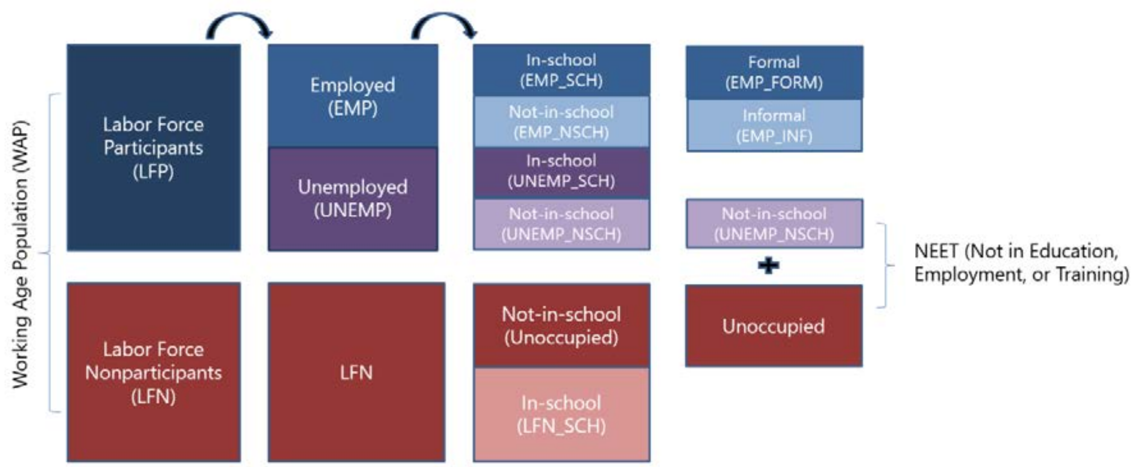
B. Variable Definitions

Labor market statuses and their interrelationships are detailed in Figure 1.1. In general, youth includes individuals aged 15-24 years old, while adult includes individuals aged 25-64 years old. Together, these constitute the working age population (WAP). Amongst the WAP, individuals at each point in time are either participating in the labor force (LFP) or out of the labor force/non-participating (LFN). The labor force includes employed (either formal or informal) and unemployed individuals. It is possible to be in the labor force and attending school. However, Individuals outside of the labor force (LFN) can either be in school or not, and those that are not in school are considered unoccupied. Given these categories, the labor force participation and employment rates are defined as the ratio of the labor force or employment to the relevant demographic group population. The unemployment rates are expressed as a percent of the relevant demographic group labor force. Finally, the share of youth not in employment, education or training (NEET) or youth inactivity rate is defined as the ratio of unoccupied and out-of-school unemployed young individuals to the total youth population.

[1] Prepared by Daniela Muhaj.

Informal employment per the ILO is defined as inclusive of: (1) own account workers (self-employed with no employees) in informal sector enterprises; (2) employers (self-employed with employees) in informal sector enterprises; (3) contributing family workers (regardless of enterprise type); (4) members of informal producers' cooperatives; (5) employees in informal jobs (i.e., jobs not subject to national legislation regarding the employment relationship); and (6) own account workers engaged in goods production only for their own household's use. Informal sector enterprises may be roughly characterized as private, unincorporated enterprises for which no complete accounts are available. *Formal employment* is the complementary employment state to informal.

Figure 1.1. Breakdown of Labor Market Outcomes



Sources: ILO and IMF staff.
Notes: See current ILO guidelines for complete definitions regarding the labor force and employment. Note that labor force nonparticipants may also be designated as economically active. Furthermore, the unoccupied status may include volunteer or unpaid work outside of market-based employment (such as home production).

C. Data Sources

Population statistics at the country-level (tabulated by age and gender) are taken from the United Nations' annual World Population Projections. Labor market indicators are collected from the International Labor Organization Statistics (ILOSTAT) Yearly Indicators (YI) database. Structural policy indicators and characteristics are drawn from a variety of sources. Due to the limited time coverage for many of these variables and since structural policies and characteristics typically change only slowly over time, the focus in the analysis is on the cross-sectional variation, as captured by the average (mean) by country of the structural policy indicators and characteristics over the available data. See Table 1.2 for details on the set of structural variables considered, along with some summary statistics.

Microeconomic data sources used in the analysis—individual-level data from national censuses and cross-country surveys—are detailed in subsequent chapters.

D. Further Stylized Facts

Based on these data, further stylized facts are dicussed here that complement those described in the main note.

Pyramids of current and projected working age populations for the average country by economy or regional EMDE group, broken down by age and gender, show the diverse demographic challenges facing countries (Figure 1.2). The average AE and average EMDE in Emerging Europe and Centra Asia are expected to see the greatest pressures from population aging, with their pyramids becoming even more inverted. By contrast, the pyramids for average EMDEs elsewhere are expected to remain expansive (wider bases than tops), although with noticeable narrowing in some cases (South and East Asia and Latin America and the Caribbean). The average EMDE in sub-Saharan Africa has the most expansive pyramid , shifting only a little.

As illustrated in the main report, *youth labor force participation* rates in the average EMDE are similar to the average AE, at about 40 percent, having gradually declined over time due largely to the rise in school enrollment over the past 25 years. That said, non-participants are about 15 percent less likely to be in school in the average EMDE than they are in the average AE.[2] Furthermore, comparing young men and women's participation rates, the gap remains large in the average EMDE, at about 20 percentage points, while in the average AE, they have become nearly identical (Figure 1.3, panel 1). In levels, young women's labor force participation in the average EMDE is now around 30 percent, about 20 percentage points below that for young men.

Youth employment rates exhibit a slightly smaller gender gap of about 15 percentage points (Figure 1.3, panel 2). In general, these gender differences among youth are smaller than those observed for the broader working age population though, where women's participation and employment rates are still about 30 and 20 percentage points below men's, respectively. This points to some improvement over time.

Youth unemployment rates are about twice as high as those of the working age population, at around 18 percent in the average EMDE (versus 12 percent in the average AE), underlaid by large gender gaps. Young women's unemployment rates in EMDEs tend to be both persistently higher and more volatile than young men's, unlike in AEs (Figure 1.3, panel 5). For young women, the unemployment rate in the average EMDE is now about 22 percent, while for young men, it is around 17 percent. Both have fluctuated widely, but since 1990 the average volatility across EMDEs for young women's unemployment was about 30 percent higher, suggesting that their employment attachment is more fragile. As with other labor market aspects, there is also a large

[2] This is based on a back-of-the-envelope calculation using the youth labor force participation rate, youth unemployment rate, and the NEET rate, where schooling is assumed to be the complementary out-of-the-labor-force state to being unoccupied.

degree of variation across EMDEs, with the current interquartile range for young women's unemployment about 20 percentage points and for young men about 15 percentage points. Unemployment rates for women and men in the broader working age population are lower and their variability, both over time and across countries, is also lower, but a persistent gender gap is still evident. By contrast, this unemployment gender gap is largely closed in the average AE; among youth, women's unemployment is routinely 1 to 2 percentage points lower than men's.

At around 20 percent, the *NEET rate* or youth inactivity rate in the average EMDE is double that in the average AE. This partly reflects a large disparity by gender in EMDEs—the NEET rate is about 10 percentage points higher for young women than men, while nearly the same in AEs (Figure 1.3, panel 6). Over the past decade, there has been only a small decline in the NEET gender gap in the average EMDE. At the same time, the average differences across geographic regions in school enrollment by gender have come down or vanished, particularly for secondary school enrollment (Figure 1.3, panels 3-4). In fact, it appears that young women's enrollment is now outstripping young men's in some cases, notably for tertiary education in emerging Europe. However, there is a large degree of country variation underlying these median gap estimates, with some countries exhibiting still very large school enrollment gaps.

Table 1.1. Country Groups and Sample Coverage

Country	ISO Code	IFS Code	WEO Country Group	WB Geographic Group	IPUMS Group	Analytical Samples			
						Okun's Law	IPUMS	SWTS	LiTS
Albania	ALB	914	EMDE (non-LIDC)	Europe & Central Asia		X			X
Algeria	DZA	612	EMDE (non-LIDC)	Middle East & North Africa					
Angola	AGO	614	EMDE (non-LIDC)	Sub-Saharan Africa					
Argentina	ARG	213	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Armenia	ARM	911	EMDE (non-LIDC)	Europe & Central Asia	EUM	X	X	X	X
Azerbaijan	AZE	912	EMDE (non-LIDC)	Europe & Central Asia		X			X
Bahamas, The	BHS	313	EMDE (non-LIDC)	Latin America & the Caribbean					
Bahrain	BHR	419	EMDE (non-LIDC)	Middle East & North Africa					
Barbados	BRB	316	EMDE (non-LIDC)	Latin America & the Caribbean		X			
Belarus	BLR	913	EMDE (non-LIDC)	Europe & Central Asia					X
Belize	BLZ	339	EMDE (non-LIDC)	Latin America & the Caribbean		X			
Bolivia	BOL	218	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Bosnia and Herzegovina	BIH	963	EMDE (non-LIDC)	Europe & Central Asia		X			X
Botswana	BWA	616	EMDE (non-LIDC)	Sub-Saharan Africa	SSA	X	X		
Brazil	BRA	223	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X	X	
Brunei Darussalam	BRN	516	EMDE (non-LIDC)	East Asia & Pacific					
Bulgaria	BGR	918	EMDE (non-LIDC)	Europe & Central Asia		X			X
Cabo Verde	CPV	624	EMDE (non-LIDC)	Sub-Saharan Africa					
Chile	CHL	228	EMDE (non-LIDC)	Latin America & the Caribbean		X			
China	CHN	924	EMDE (non-LIDC)	East Asia & Pacific					
Colombia	COL	233	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Costa Rica	CRI	238	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Croatia	HRV	960	EMDE (non-LIDC)	Europe & Central Asia		X			X
Dominican Republic	DOM	243	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X	X	
Ecuador	ECU	248	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Egypt	EGY	469	EMDE (non-LIDC)	Middle East & North Africa		X		X	
El Salvador	SLV	253	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Equatorial Guinea	GNQ	642	EMDE (non-LIDC)	Sub-Saharan Africa					
Fiji	FJI	819	EMDE (non-LIDC)	East Asia & Pacific	SEA		X		
FYR Macedonia	MKD	962	EMDE (non-LIDC)	Europe & Central Asia		X		X	X

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Country	ISO Code	IFS Code	WEO Country Group	WB Geographic Group	IPUMS Group	Analytical Samples			
						Okun's Law	IPUMS	SWTS	LiTS
Gabon	GAB	646	EMDE (non-LIDC)	Sub-Saharan Africa					
Georgia	GEO	915	EMDE (non-LIDC)	Europe & Central Asia		X			X
Guatemala	GTM	258	EMDE (non-LIDC)	Latin America & the Caribbean		X			
Guyana	GUY	336	EMDE (non-LIDC)	Latin America & the Caribbean					
Hungary	HUN	944	EMDE (non-LIDC)	Europe & Central Asia	EUM	X	X		X
India	IND	534	EMDE (non-LIDC)	South Asia	SEA		X		
Indonesia	IDN	536	EMDE (non-LIDC)	East Asia & Pacific	SEA	X	X		
Iran	IRN	429	EMDE (non-LIDC)	Middle East & North Africa	EUM	X	X		
Iraq	IRQ	433	EMDE (non-LIDC)	Middle East & North Africa					
Jamaica	JAM	343	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X	X	
Jordan	JOR	439	EMDE (non-LIDC)	Middle East & North Africa				X	
Kazakhstan	KAZ	916	EMDE (non-LIDC)	Europe & Central Asia					X
Kuwait	KWT	443	EMDE (non-LIDC)	Middle East & North Africa					
Lebanon	LBN	446	EMDE (non-LIDC)	Middle East & North Africa				X	
Libya	LBY	672	EMDE (non-LIDC)	Middle East & North Africa					
Malaysia	MYS	548	EMDE (non-LIDC)	East Asia & Pacific	SEA		X		
Maldives	MDV	556	EMDE (non-LIDC)	South Asia					
Mauritius	MUS	684	EMDE (non-LIDC)	Sub-Saharan Africa		X			
Mexico	MEX	273	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Mongolia	MNG	948	EMDE (non-LIDC)	East Asia & Pacific		X			X
Montenegro	MNE	943	EMDE (non-LIDC)	Europe & Central Asia		X			X
Morocco	MAR	686	EMDE (non-LIDC)	Middle East & North Africa		X			
Namibia	NAM	728	EMDE (non-LIDC)	Sub-Saharan Africa					
Oman	OMN	449	EMDE (non-LIDC)	Middle East & North Africa					
Pakistan	PAK	564	EMDE (non-LIDC)	South Asia		X			
Panama	PAN	283	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Paraguay	PRY	288	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Peru	PER	293	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Philippines	PHL	566	EMDE (non-LIDC)	East Asia & Pacific		X			
Poland	POL	964	EMDE (non-LIDC)	Europe & Central Asia		X			X

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Country	ISO Code	IFS Code	WEO Country Group	WB Geographic Group	IPUMS Group	Analytical Samples			
						Okun's Law	IPUMS	SWTS	LiTS
Qatar	QAT	453	EMDE (non-LIDC)	Middle East & North Africa		X			
Romania	ROU	968	EMDE (non-LIDC)	Europe & Central Asia	EUM	X	X		
Russia	RUS	922	EMDE (non-LIDC)	Europe & Central Asia		X			X
Samoa	WSM	862	EMDE (non-LIDC)	East Asia & Pacific					
Saudi Arabia	SAU	456	EMDE (non-LIDC)	Middle East & North Africa		X			
Serbia	SRB	942	EMDE (non-LIDC)	Europe & Central Asia		X		X	X
South Africa	ZAF	199	EMDE (non-LIDC)	Sub-Saharan Africa	SSA	X	X		
Sri Lanka	LKA	524	EMDE (non-LIDC)	South Asia		X			
St. Lucia	LCA	362	EMDE (non-LIDC)	Latin America & the Caribbean					
St. Vincent and the Grenadines	VCT	364	EMDE (non-LIDC)	Latin America & the Caribbean					
Suriname	SUR	366	EMDE (non-LIDC)	Latin America & the Caribbean		X			
Swaziland	SWZ	734	EMDE (non-LIDC)	Sub-Saharan Africa					
Syria	SYR	463	EMDE (non-LIDC)	Middle East & North Africa					
Thailand	THA	578	EMDE (non-LIDC)	East Asia & Pacific		X			
Tonga	TON	866	EMDE (non-LIDC)	East Asia & Pacific					
Trinidad and Tobago	TTO	369	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Tunisia	TUN	744	EMDE (non-LIDC)	Middle East & North Africa		X			
Turkey	TUR	186	EMDE (non-LIDC)	Europe & Central Asia		X			X
Turkmenistan	TKM	925	EMDE (non-LIDC)	Europe & Central Asia					
Ukraine	UKR	926	EMDE (non-LIDC)	Europe & Central Asia				X	X
United Arab Emirates	ARE	466	EMDE (non-LIDC)	Middle East & North Africa					
Uruguay	URY	298	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Vanuatu	VUT	846	EMDE (non-LIDC)	East Asia & Pacific					
Venezuela	VEN	299	EMDE (non-LIDC)	Latin America & the Caribbean	LAC	X	X		
Afghanistan	AFG	512	EMDE (LIDC)	South Asia					
Bangladesh	BGD	513	EMDE (LIDC)	South Asia	SEA	X	X		
Benin	BEN	638	EMDE (LIDC)	Sub-Saharan Africa				X	
Bhutan	BTN	514	EMDE (LIDC)	South Asia		X			
Burkina Faso	BFA	748	EMDE (LIDC)	Sub-Saharan Africa	SSA		X		
Burundi	BDI	618	EMDE (LIDC)	Sub-Saharan Africa					

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Country	ISO Code	IFS Code	WEO Country Group	WB Geographic Group	IPUMS Group	Analytical Samples			
						Okun's Law	IPUMS	SWTS	LiTS
Cambodia	KHM	522	EMDE (LIDC)	East Asia & Pacific	SEA		X	X	
Cameroon	CMR	622	EMDE (LIDC)	Sub-Saharan Africa					
Chad	TCD	628	EMDE (LIDC)	Sub-Saharan Africa					
Comoros	COM	632	EMDE (LIDC)	Sub-Saharan Africa					
Congo, Dem. Rep.	COD	636	EMDE (LIDC)	Sub-Saharan Africa					
Congo, Rep.	COG	634	EMDE (LIDC)	Sub-Saharan Africa				X	
Cote D'Ivoire	CIV	662	EMDE (LIDC)	Sub-Saharan Africa					
Djibouti	DJI	611	EMDE (LIDC)	Middle East & North Africa					
Ethiopia	ETH	644	EMDE (LIDC)	Sub-Saharan Africa		X			
Gambia, The	GMB	648	EMDE (LIDC)	Sub-Saharan Africa					
Ghana	GHA	652	EMDE (LIDC)	Sub-Saharan Africa	SSA		X		
Guinea	GIN	656	EMDE (LIDC)	Sub-Saharan Africa					
Haiti	HTI	263	EMDE (LIDC)	Latin America & the Caribbean					
Honduras	HND	268	EMDE (LIDC)	Latin America & the Caribbean		X			
Kenya	KEN	664	EMDE (LIDC)	Sub-Saharan Africa					
Kyrgyz Republic	KGZ	917	EMDE (LIDC)	Europe & Central Asia	EUM	X	X		X
Lao P.D.R.	LAO	544	EMDE (LIDC)	East Asia & Pacific					
Lesotho	LSO	666	EMDE (LIDC)	Sub-Saharan Africa					
Liberia	LBR	668	EMDE (LIDC)	Sub-Saharan Africa				X	
Madagascar	MDG	674	EMDE (LIDC)	Sub-Saharan Africa				X	
Malawi	MWI	676	EMDE (LIDC)	Sub-Saharan Africa	SSA		X	X	
Mali	MLI	678	EMDE (LIDC)	Sub-Saharan Africa	SSA		X		
Mauritania	MRT	682	EMDE (LIDC)	Sub-Saharan Africa					
Moldova	MDA	921	EMDE (LIDC)	Europe & Central Asia		X			X
Mozambique	MOZ	688	EMDE (LIDC)	Sub-Saharan Africa					
Myanmar	MMR	518	EMDE (LIDC)	East Asia & Pacific					
Nepal	NPL	558	EMDE (LIDC)	South Asia				X	
Nicaragua	NIC	278	EMDE (LIDC)	Latin America & the Caribbean	LAC		X		
Niger	NER	692	EMDE (LIDC)	Sub-Saharan Africa					
Nigeria	NGA	694	EMDE (LIDC)	Sub-Saharan Africa					

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Country	ISO Code	IFS Code	WEO Country Group	WB Geographic Group	IPUMS Group	Analytical Samples: Okun's Law	Analytical Samples: IPUMS	Analytical Samples: SWTS	Analytical Samples: LiTS
Papua New Guinea	PNG	853	EMDE (LIDC)	East Asia & Pacific					
Rwanda	RWA	714	EMDE (LIDC)	Sub-Saharan Africa					
Sao Tome and Principe	STP	716	EMDE (LIDC)	Sub-Saharan Africa					
Senegal	SEN	722	EMDE (LIDC)	Sub-Saharan Africa					
Sierra Leone	SLE	724	EMDE (LIDC)	Sub-Saharan Africa					
Solomon Islands	SLB	813	EMDE (LIDC)	East Asia & Pacific					
Sudan	SDN	732	EMDE (LIDC)	Sub-Saharan Africa					
Tajikistan	TJK	923	EMDE (LIDC)	Europe & Central Asia					X
Tanzania	TZA	738	EMDE (LIDC)	Sub-Saharan Africa	SSA		X	X	
Timor-Leste	TLS	537	EMDE (LIDC)	East Asia & Pacific					
Togo	TGO	742	EMDE (LIDC)	Sub-Saharan Africa				X	
Uganda	UGA	746	EMDE (LIDC)	Sub-Saharan Africa	SSA		X		
Uzbekistan	UZB	927	EMDE (LIDC)	Europe & Central Asia					X
Vietnam	VNM	582	EMDE (LIDC)	East Asia & Pacific	SEA		X	X	
Yemen	YEM	474	EMDE (LIDC)	Middle East & North Africa					
Zambia	ZMB	754	EMDE (LIDC)	Sub-Saharan Africa	SSA		X	X	
Zimbabwe	ZWE	698	EMDE (LIDC)	Sub-Saharan Africa		X			
Australia	AUS	193	AE	Advanced Economies		X			
Austria	AUT	122	AE	Advanced Economies	AE	X	X		
Belgium	BEL	124	AE	Advanced Economies		X			
Canada	CAN	156	AE	Advanced Economies		X			
Cyprus	CYP	423	AE	Advanced Economies		X			
Czech Republic	CZE	935	AE	Advanced Economies		X			
Denmark	DNK	128	AE	Advanced Economies		X			
Estonia	EST	939	AE	Advanced Economies		X			
Finland	FIN	172	AE	Advanced Economies		X			
France	FRA	132	AE	Advanced Economies	AE	X	X		
Germany	DEU	134	AE	Advanced Economies		X			
Greece	GRC	174	AE	Advanced Economies		X			
Hong Kong SAR	HKG	532	AE	Advanced Economies		X			

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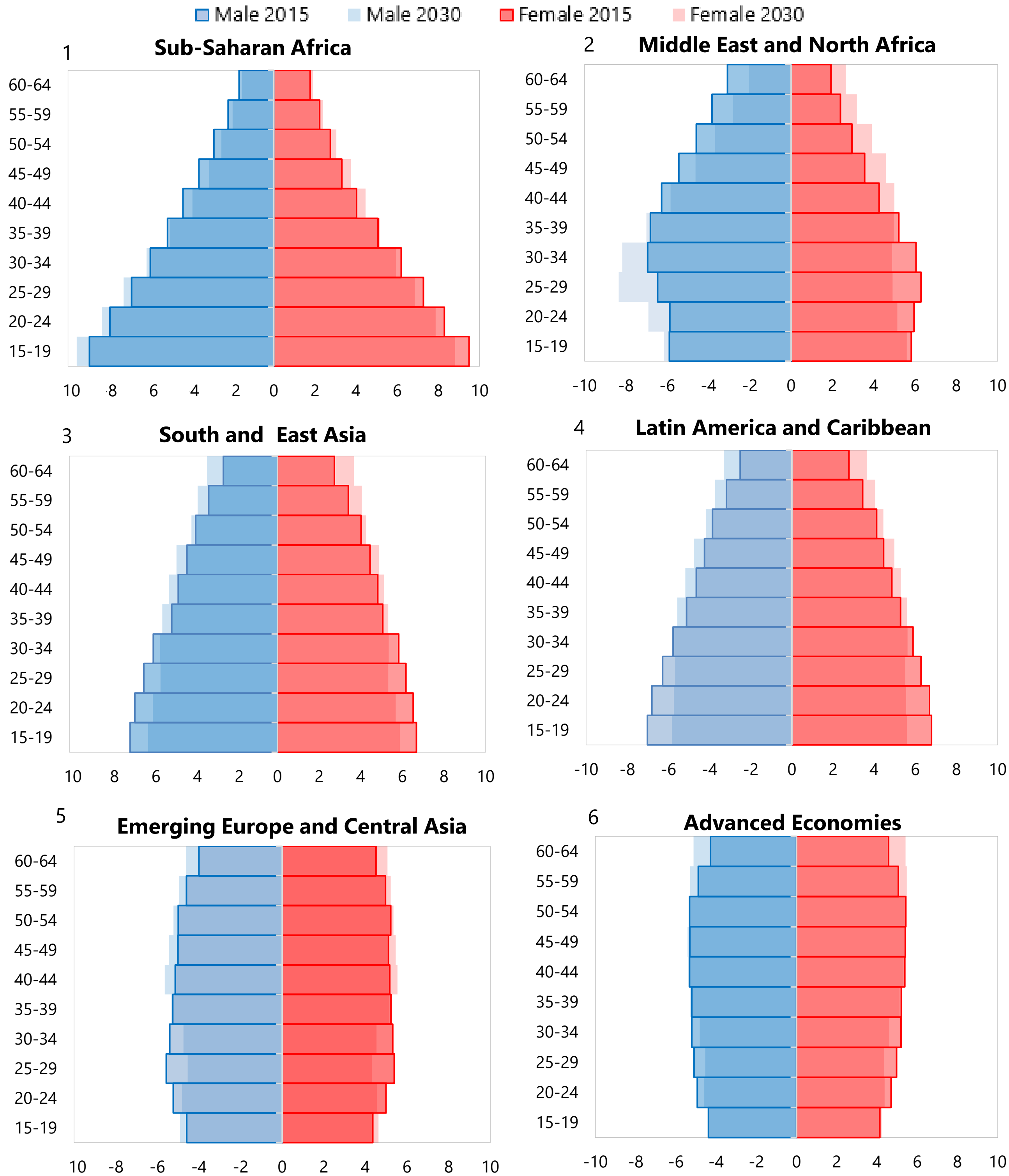
Country	ISO Code	IFS Code	WEO Country Group	WB Geographic Group	IPUMS Group	Analytical Samples			
						Okun's Law	IPUMS	SWTS	LiTS
Iceland	ISL	176	AE	Advanced Economies		X			
Ireland	IRL	178	AE	Advanced Economies		X			
Israel	ISR	436	AE	Advanced Economies		X			
Italy	ITA	136	AE	Advanced Economies		X			
Japan	JPN	158	AE	Advanced Economies		X			
Korea	KOR	542	AE	Advanced Economies		X			
Latvia	LVA	941	AE	Advanced Economies		X			
Lithuania	LTU	946	AE	Advanced Economies		X			
Luxembourg	LUX	137	AE	Advanced Economies		X			
Macao SAR	MAC	546	AE	Advanced Economies		X			
Malta	MLT	181	AE	Advanced Economies		X			
Netherlands	NLD	138	AE	Advanced Economies		X			
New Zealand	NZL	196	AE	Advanced Economies		X			
Norway	NOR	142	AE	Advanced Economies		X			
Portugal	PRT	182	AE	Advanced Economies	AE	X	X		
Puerto Rico	PRI	359	AE	Advanced Economies		X			
Singapore	SGP	576	AE	Advanced Economies		X			
Slovak Republic	SVK	936	AE	Advanced Economies		X			
Slovenia	SVN	961	AE	Advanced Economies		X			
Spain	ESP	184	AE	Advanced Economies	AE	X	X		
Sweden	SWE	144	AE	Advanced Economies		X			
Switzerland	CHE	146	AE	Advanced Economies	AE	X	X		
Taiwan Province of China	TWN	528	AE	Advanced Economies		X			
United Kingdom	GBR	112	AE	Advanced Economies		X			
United States	USA	111	AE	Advanced Economies	AE	X	X		

Source: IMF WEO, World Bank, and IMF staff.

Note: Countries appear above if they are included in the samples underlying the stylized facts taken from ILOSTAT. Analytical samples are drawn from the indicated source data or in the case of the Okun's Law sample, underlying data are youth and adult unemployment from ILOSTAT. AE: Advanced Economies, SSA: Sub-Saharan Africa, EUM: Emerging Europe and Middle East, SEA: South-East Asia and the Pacific, LAC: Latin America and Caribbean.

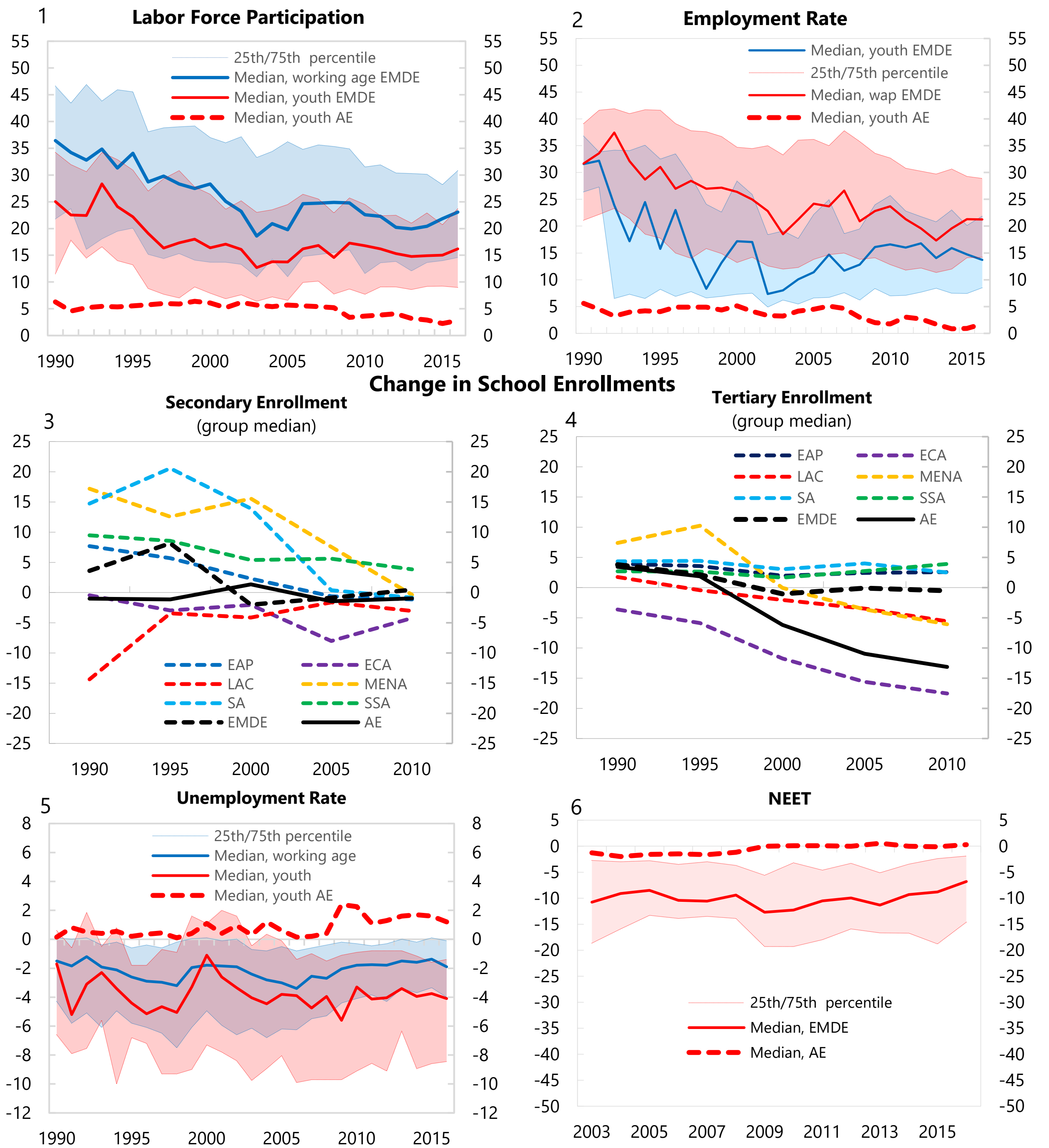
Figure 1.2. Population Age Pyramids
(percent of working age population)



Sources: UN DESA Population and IMF staff calculations (2017).

Figure 1.3. Gender Differences in Youth Labor Markets

(male minus female, percentage points)



Sources: ILO Yearly Indicators, Lee and Lee (2016) Long-Run Education Dataset, and IMF staff calculations.

Note: The gender difference is calculated as the male minus female value of the indicator. Labor force participation, employment rates and the NEET are expressed as a percent of the relevant demographic group population. Unemployment rates are expressed as a percent of the relevant demographic group labor force. Percentiles are calculated from the sample of countries in the indicated group. AE: Advanced Economies; EAP: East Asia & Pacific; ECA: Europe & Central Asia; EMDE: Emerging Markets & Developing Economies; LAC: Latin America & Caribbean; MENA: Middle East & North Africa; SA: South Asia; SSA: Sub-Saharan Africa.

Table 1.2. Structural Indicator Definitions and Descriptive Statistics

	Indicator (Units)	Mean	Standard deviation	Median	25th percentile	75th percentile	Min	Max	N	Source
Labor Market	Labor market regulation index *(0-1; higher tighter)*	0.69	0.14	0.71	0.61	0.79	0.28	0.98	90	IMF (2018)
	Unemployment benefit coverage share *(percentage points)*	26.23	36.47	11.05	0.00	44.56	0.00	235.22	86	Aleksynska and Schindler (2011)
	Unemployment benefit replacement rate *(percentage points)*	13.89	16.12	8.86	0.00	23.61	0.00	60.44	90	Aleksynska and Schindler (2011)
	Minimum wage to mean wage ratio *(percentage points)*	0.36	0.18	0.35	0.23	0.53	0.00	0.76	75	Aleksynska and Schindler (2011)
	Employment protection legislation, severance pay *(0-1; higher more protection)*	0.17	0.22	0.06	0.00	0.24	0.00	0.91	95	ILO (2015a) EPLex
Product Market	Product market regulation index *(0-1; higher tighter)*	0.44	0.18	0.46	0.30	0.57	0.00	0.94	90	IMF (2018)
	Cost of starting a business *(% of income per capita)*	53.75	94.94	18.65	6.59	56.00	0.05	786.52	186	WBG, Doing Business
	Starting business distance to frontier score *(0-100; higher closer to frontier)*	71.98	17.03	75.91	65.26	84.43	22.13	98.15	186	WBG, Doing Business
Other	Share of total economy informal employment *(percent)*	71.60	21.03	77.05	57.89	88.60	22.33	99.70	42	ILOSTAT
	Index of legal protections for women *(0 to 1; higher more protection)* 1/	0.59	0.22	0.58	0.50	0.79	0.17	1.00	187	WBG, WDI
	Log public health expenditure per capita *(real PPP)*	5.92	1.32	5.98	4.88	6.85	2.87	8.73	187	WBG, WDI
	Social safety net coverage *(percent of population)*	30.05	24.64	24.85	7.96	47.12	0.24	92.26	110	WBG, WDI
	Average tariff rate weighted by industry share *(percent)*	7.58	4.97	6.65	2.78	11.02	0.00	22.20	181	WBG, WITS
	Trade openness *(percent)* 2/	84.75	44.31	77.15	52.58	108.64	20.39	344.43	190	Penn World Table 8.1

Note: 1/ The index of women's legal protections is the simple average of six binary country-level indicators (1 for yes, 0 for no) on the existence of protections for women in the labor market along the following dimensions: (1) no gender restrictions on jobs; (2) prohibitions against child or early marriage; (3) equal pay for equal value work required; (4) maternity leave required (paid or unpaid); (5) gender nondiscrimination in hiring required; and (6) no discrimination in work after end of maternity leave. 2/Trade openness is defined as the ratio of the sum of exports plus imports to GDP.

DEMAND CONDITIONS AND YOUTH UNEMPLOYMENT IN EMERGING MARKET AND DEVELOPING ECONOMIES[1]

A. Introduction

Starting with Okun (1962), a rich empirical literature has documented the existence of a negative relationship between an economy's aggregate demand conditions and its overall unemployment. This empirical regularity, known as Okun's law, is expressed as a negative statistical association between the cyclical component of the unemployment rate (henceforth unemployment gap), defined as the percentage point difference between the realized and "natural" or long-term equilibrium unemployment rates, and the output gap, defined as the percent difference between the economy's real GDP and its "natural" or long-term level. Okun (1962) studied this relationship for the United States. Subsequent analyses have found this law to hold across a broad set of economies, but more strongly in AEs than EMDEs (Ball, Leigh, and Loungani 2017; An, Ghazi, and Prieto 2017; Ball and others 2016). Banerji and others (2014) and Banerji, Lin, and Saksonovs (2015) focused on youth in advanced European countries and found that their unemployment is more sensitive to the business cycle than that of adults, reflecting their relatively more fragile employment connection.

Much less is known about the validity and the strength of the Okun's law for youth in EMDEs, including vis-à-vis adults, and the current analysis attempts to shed some light on this issue.[2] In a first step, we investigate the average statistical relationship between the output gap and the unemployment gap for both youth (defined as those aged between 15 and 24) and adults (aged between 25 and 64) in a panel of 58 middle- and low-income developing countries.[3] In order to draw some comparisons, we analyze the same relationship in a panel of 38 high-income economies. In a second step, we check whether changes in cyclical conditions have different effects on unemployment depending on the stage of the business cycle. Finally, we explore potential country heterogeneities in the relationship between aggregate demand and unemployment and investigate possible determinants.

As described in the main note, we find that the youth unemployment rate in EMDEs is twice as sensitive to the cycle as that of adults, but both are about half as sensitive as the corresponding rates in AEs. Quantitatively, the youth unemployment rate for the typical EMDE is estimated to be

[1] Prepared by Zidong An and Gabriele Ciminelli.

[2] In a recent contribution, Hutengs and Stadtmann (2013) examine the cyclical sensitivity of youth unemployment for five emerging market EU members, comparing it to those of advanced Europe (EU-15). They find a pattern for emerging Europe similar to that for advanced Europe—youth unemployment is more cyclically sensitive than that of older cohorts.

[3] As in much of the analysis, poor sample coverage prevents undertaking a separate analysis of Okun's law for the group of low-income developing countries (LIDCs). The results here are from a sample that pools EMDEs.

about 0.3 percentage points lower for each 1 percentage point rise in the output gap. Other main findings include:

- Downturns are disproportionately detrimental to youth in EMDEs—they raise the unemployment rate by about twice as much as upturns lower it. For adults in EMDEs, the ratio between the cyclical sensitivity of unemployment during downturns and upturns is about 1.5 (versus 2 for youth). However, the cyclical sensitivities of unemployment rates in EMDEs are statistically indistinguishable between upturns and downturns, while equality can be rejected in AEs (for both youth and adults).
- The cyclical sensitivity of unemployment exhibits great variability across countries. For example, for Indonesia and Ukraine we estimate near zero cyclical sensitivities of youth unemployment, while Brazil and Colombia are close to the average sensitivity in AEs. Cross-country heterogeneity in EMDEs is strongly associated with the level of informality in employment.

How important is the cycle in explaining unemployment variability in EMDEs? The results suggest that it accounts for less of the overall variation in EMDEs' youth unemployment than it does in AEs. Further analysis suggests that high levels of informality in employment in EMDEs compared to AEs may partly account for this—by providing the outside option of self- (informal) employment, higher informality provides some buffer to the impact of overall business conditions on both youth and adult unemployment rates (see also Loayza and Rigolini, 2011).

Turning to the finding of a larger response of unemployment to changes in demand conditions during downturns relative to upturns, this is consistent with the presence of downward nominal and real wage rigidities, which make labor demand more responsive to downturns. The fact that we do not find a statistically significant difference between downturns and upturns for EMDEs may be due the greater noisiness of their data, but it is also consistent with the fact that real wage rigidities are more prominent in AE labor markets (partly explained by the presence of greater job formality and more extensive labor market regulations).

These findings have implications for policies. As EMDEs continue to develop, informality in employment is likely to fall, encouraging a welcome rise in the share of higher productivity, higher paying jobs. At the same time however, informal jobs would play a smaller role in buffering the employment impact of macroeconomic fluctuations, resulting in higher cyclical sensitivities of youth and adult unemployment. Expanding the social safety net would help address the need for income insurance associated with greater sensitivity, although unemployment benefit systems should be carefully designed to provide strong incentives for formal job search and maintain high overall employment (Setty, 2017; Duval and Loungani, 2018). At the same time, the estimated asymmetric sensitivity of unemployment to the cycle, with downturns more influential, supports the argument that policymakers in EMDEs should build buffers in upturns to be able to undertake countercyclical policies in downturns.

The rest of the Chapter is structured as follows: section B discusses the econometric methodology; section C describes the data; and section D presents the results.

B. Methodology

We follow Ball, Leigh, and Loungani (2017) and estimate the Okun's law specification in gaps for our baseline model:

$$u_{i,t} - u^*_{i,t} = \beta\left(y_{i,t} - y^*_{i,t}\right) + \mu_i + \varepsilon_{i,t} \tag{1}$$

where $u_{i,t}$ is the unemployment rate of country i in year t, $y_{i,t}$ is the log of real GDP, and * indicates their long-run or natural levels. The Okun coefficient β measures the short-run responsiveness of the unemployment gap (that is the difference between the unemployment rate and its natural level) to the output gap (similarly defined as the difference between output and its natural level). It is expected to be negative—tighter demand conditions lead to tighter labor market conditions.

Unlike Ball, Leigh, and Loungani (2017), where Okun coefficients are estimated country-by-country, we pool and estimate a panel regression with country fixed effects (μ_i). The panel regression allows us to overcome limited data coverage in EMDEs, but assumes the same Okun coefficient among countries. By including country fixed effects, we control for any time-invariant characteristics that could affect both the unemployment gap and output gap.[4] The estimation is done through ordinary least squares with robust standard errors clustered at the country level.

While the primary focus of our analysis is on youth unemployment, we also estimate the same specification for adult unemployment to enable comparisons of the two groups. We also run the same estimations for the sample of AEs to see if there are differences in sensitivity related to the overall level of economic development.

In an alternative specification, we investigate whether the responsiveness of the unemployment rate to output fluctuations is symmetric across cyclical upturns and downturns, defined respectively as periods of positive and negative output gaps. To do so, we extend Equation (1) as follows:

$$u_{i,t} - u^*_{i,t} = \beta^u d^u_{i,t}\left(y_{i,t} - y^*_{i,t}\right) + \beta^d\left(1 - d^u_{i,t}\right)\left(y_{i,t} - y^*_{i,t}\right) + \mu_i + \varepsilon_{i,t} \tag{2}$$

where $d^g_{i,t}$ is a dummy taking value one in upturns and zero otherwise. Specifically, we estimate potential output ($y^*_{i,t}$) with the Hodrick-Prescott filter and define $d^u_{i,t}$ as one if actual output is greater than potential and zero otherwise. The coefficients β^u and β^d measure the short-run responsiveness of the unemployment rate to the output gap during upturns and downturns,

[4] We also considered specifications with no fixed-effects and those with both country and time fixed effects. The results are robust to these alternatives.

respectively. The rest is as in Equation (1). Under the null hypothesis of symmetric responsiveness, β^u and β^d are not statistically different from each other. We test this hypothesis with a Wald test (H0 β^u=β^d), carrying out the same tests for both youth and adult samples in EMDEs and AEs.

Cross-Country Heterogeneity

Recent studies have found a high degree of heterogeneity in the responsiveness of the overall unemployment rate to output fluctuations in both AEs and EMDEs (Ball, Leigh, and Loungani 2017, and Ball, Furceri, Leigh, and Loungani 2016). Banerji, Lin, and Saksonovs (2015) also found heterogeneous Okun coefficients for youth unemployment rates across advanced European countries. Therefore, we complement our baseline, pooled analysis, by also estimating country-specific Okun coefficients. We follow Banerji, Lin, and Saksonovs (2015) and interact the output gap with country dummies as follows:

$$u_{i,t} - u^*_{i,t} = \sum_{j=1}^{J} \beta^j c^j \left(y_{i,t} - y^*_{i,t}\right) + \mu_i + \varepsilon_{i,t} \tag{3}$$

where c^j are the country dummies, taking value one if $j = i$, for $j = 1, \dots, J$. The Okun coefficients β^j measure the country-specific contemporaneous responsiveness of the unemployment gap to the output gap in country j. As expected, due to the limited sample coverage at the individual country-level, the estimates often have poor precision—see section D.

Next, we explore the role of individual countries' structural characteristics and policies for the responsiveness of unemployment to output fluctuations. As a compromise between fully pooled and fully independent country estimates of Okun coefficients, we modify Equation (1) and add an interaction term between the output gap and a variety of indicators of country structural characteristics and policies (one at a time):

$$u_{i,t} - u^*_{i,t} = \left(\beta^k + \gamma^k x_i^k\right)\left(y_{i,t} - y^*_{i,t}\right) + \mu_i + \varepsilon_{i,t} \tag{4}$$

where x_i^k is the time average of the economic characteristics or policy factor k for country i.[5] Country-specific Okun coefficients are measured by $\beta^k + \gamma^k x_i^k$, in which the parameter γ^k captures the difference in the responsiveness of the unemployment rate to the output gap due to country differences in the policies or characteristics captured by the indicator k.

C. Data

We distinguish between unemployment of youth and adults, defined respectively as individuals who are 15–24 years old and 25–64 years old. Data on unemployment come from the International Labour Organization (henceforth ILO). For comparability, estimation samples are

[5] The scarce data coverage and multicollinearity between among our structural indicators prevents us from including indicators with time dimension or including multiple indicators in the same regression.

constrained to those observations for which both adult and youth unemployment rates are available.

Table 2.1. Okun's Law: Baseline Results

	EMDEs		AEs	
	Youth (1)	**Adult (2)**	**Youth (3)**	**Adult (4)**
Okun Coef.	-0.29***	-0.14***	-0.61***	-0.26***
	(0.06)	(0.03)	(0.10)	(0.04)
R-sq.	0.12	0.11	0.45	0.43
Obs.	781	781	908	908
Panels	58	58	38	38

Source: Authors' estimation based on ILO, UN and IMF World Economic Outlook data.
Notes: This table presents estimates from Equation (1) based on panel regression with country-fixed effects. Standard errors, clustered at the country level, are in parenthesis. *, ** and *** denote respectively significance at the 10%, 5%, and 1 % confidence level.

To estimate the natural rate of unemployment by group $u^*_{i,t}$, we adopt the following algorithm. First, we linearly interpolate the unemployment rate series where there are missing observations by country. Second, we exclude from the sample all countries with less than five observations. Third, we apply the Hodrick-Prescott filter to the interpolated unemployment series and estimate its long-run level for each country. Following standard practice when using yearly data, the smoothing parameter is set to 100. Finally, we treat as missing all observations that are either isolated—preceded and followed by three or more missing observations—or for which the original ILO overall unemployment rate data is not available as missing.

Data on real GDP comes from the IMF World Economic Outlook (henceforth WEO) and does not have missing values. To estimate the natural level of output or its potential $y^*_{i,t}$ we use the log of real GDP and apply the Hodrick-Prescott filter (smooth parameter 100). We also collect data on per capita and potential GDP directly from the WEO for sensitivity analysis.

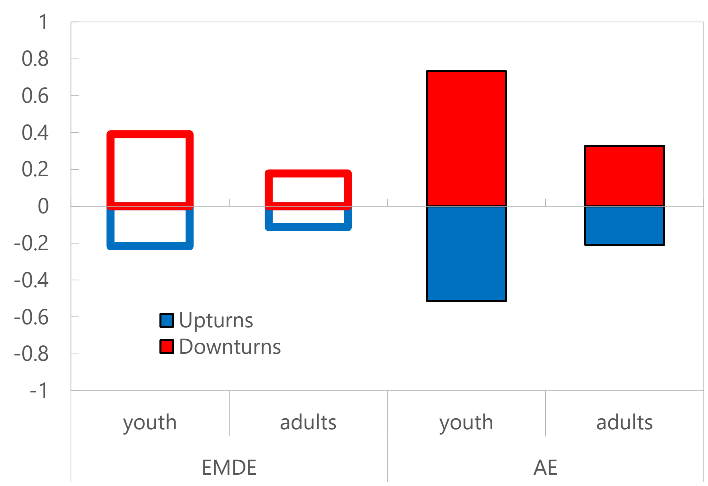
Among the structural characteristics and policy indicators we consider are: (i) labor market regulation (as an index), (ii) the unemployment benefit coverage share, (iii) the unemployment benefit replacement rate, (iv) the minimum to mean wage ratio, (v) the incidence of severance payments (as an index), (vi) legal restrictions to women employment (as an index), (vii) product market regulation (as an index), (viii) overall social spending as a share of GDP, (ix) the level of employment informality, (x) the share of imports and exports over GDP to proxy for trade openness, (xi) the exposure to routinization (as an index), and (xii) the cost of starting a business. See chapter 1 for further details.

D. Results

Table 2.1 shows the estimates from the baseline regression. For the average EMDE, the youth unemployment gap is estimated to be about 0.29 percentage lower for each 1 percentage point rise in the output gap. The sensitivity of the unemployment gap for adults is about half that of youth, at 0.14 percentage points. By contrast, for a one percentage point output gap rise in the average AE, the youth unemployment gap declines by 0.61 percentage points, while that of adults drops by 0.26 percentage points. The results for AEs are similar to those in Ball, Leigh, and Loungani (2017) for adults and Banerji, Lin, and Saksonovs (2015) for youth. The differential sensitivity to the cycle by age may reflect youth's more tenuous labor force attachment and hiring/firing decisions by firms based on experience and seniority.

These findings appear robust to a number of perturbations to the model specification and estimation sample. As a first check, we include time fixed effects to account for possible common movements in the unemployment gap that are unrelated to output. Second, we estimate the model using a measure of output gap derived from per capita GDP. Third, we remove from the sample countries that switched classification as AEs or EMDEs over the sample period. Fourth, we use the IMF WEO's potential output measure to construct the gaps. Fifth, we estimate a first-difference specification, that is using the first differences of the unemployment rate and log real GDP as dependent and explanatory variables respectively. Finally, we exclude each country one at a time to check that our results are not driven by country outliers. The estimates obtained from these robustness checks (available upon request) are comparable to the baseline.

Figure 2.1. Cyclical Sensitivity of Unemployment in Upturns and Downturns
(percentage points)

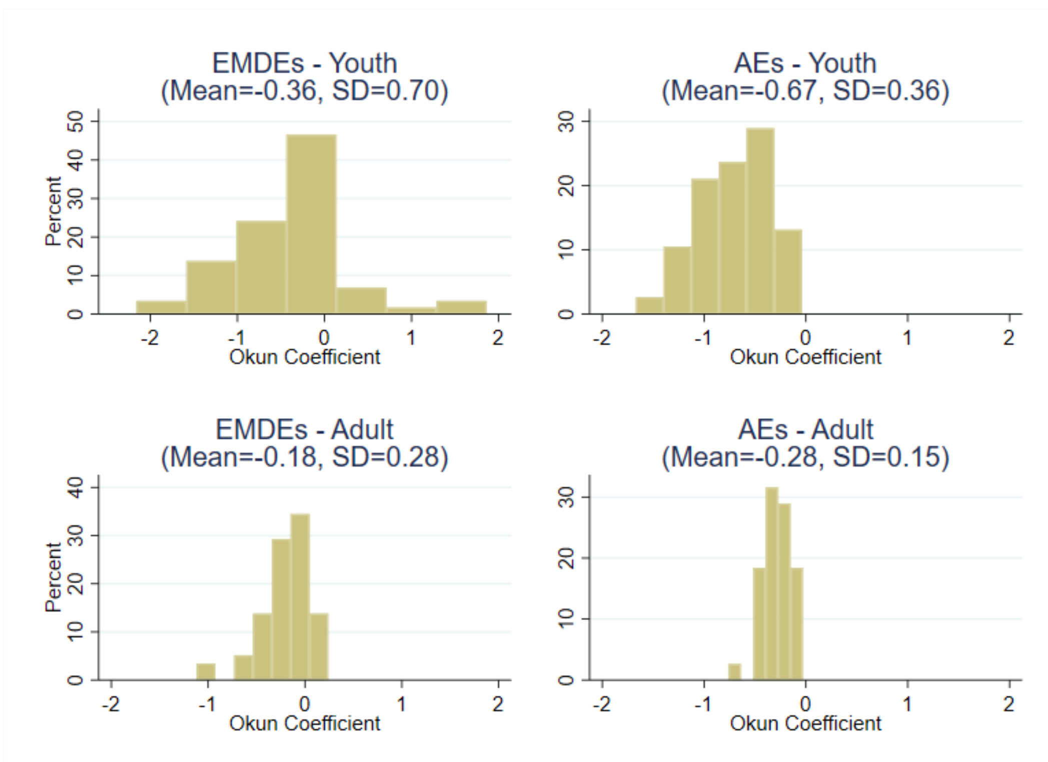


Sources: ILO Yearly Indicators, IMF World Economic Outlook (Oct. 2017), and IMF staff calculations.
Note: Estimated cyclical sensitivity of the unemployment rate gap in upturns versus downturns (one percentage point change in the output gap). Upturns (downturns) are defined as years of positive (negative) output gap. Solid-colored bars indicates that the estimated sensitivities for upturns and downturns are statistically different at the 5% level, while hollow bars indicates that they are not. All estimates shown are statistically significant at the 5% level.

Figure 2.1 provides a graphical representation of equation (2), differentiating between sensitivity to upturns and downturns. The unemployment gap rises more during periods of negative output gap than it decreases during periods of positive output gap. The ratio between the estimated coefficients is about 1.5. According to a Wald test, the cyclical sensitivities of youth and adult unemployment rates in AEs are statistically significantly different across upturns and downturns, while they are not in EMDEs. The inability to reject differences between upturns and downturns for EMDEs could be due to a weaker connection between labor market and the cycle in EMDEs as well as the greater noisiness of their data. But the results may also reflect more widespread downward nominal and real wage rigidities in AE labor markets, reflecting their more extensive labor market regulations. All else equal, such rigidities would be expected to yield larger quantity adjustment (job losses) in downturns compared to upturns.

Figure 2.2 displays histograms of the estimated country-specific Okun coefficients based on Equation (3). For EMDEs, these have average values of -0.36 and -0.18 for youth and adult unemployment rates, respectively, while the same average estimates are -0.67 and -0.28 for AEs. These average values are close to those in Table 2.1, meaning that the main findings hold even using available country-specific estimates. At the same time, there is great heterogeneity in Okun coefficients across countries and particularly so in EMDEs. For example, Indonesia and Ukraine have near zero cyclical sensitivities of youth unemployment, estimates for Brazil and Colombia

Figure 2.2. Distribution of Country-Specific Okun Coefficients



Sources: IMF staff calculations.
Note: Histograms of the estimated country-specific Okun coefficients by economy and demographic age group.

are close to the AE average, and Morocco and Zimbabwe show positive and statistically significant coefficients.[6]

Table 2.2 report estimates based on Equation (4) for youth in EMDEs, focusing only on those for which the interaction term coefficient turned out to be statistically significant. A positive (negative) and statistically significant coefficient indicates that the corresponding indicator reduced (increases) the cyclical sensitivity of unemployment. Only business start-up costs and the level of informality in employment were found to have significant associations with the Okun coefficients. Both are associated with a smaller cyclical sensitivity, thus suggesting that higher informality in employment and higher start-up costs—possibly by causing higher informality—buffer the impact of overall business conditions.[7]

Table 2.2. Determinants of Country-Specific Okun Coefficients—EMDE Youth

	(1)	(2)
Output gap	-0.389*** (0.065)	-0.903*** (0.122)
Cost of starting a business	0.456*** (0.001)	
Share of informal employment		1.043*** (0.206)
R-squared	0.15	0.24
Number of Observations	781	315
Number of Countries	58	22

Sources: ILO Yearly Indicators, IMF World Economic Outlook (Oct. 2017), World Bank Ease of Doing Business Indicators and IMF staff calculations.
Note: "Cost of starting a business" is expressed as percentage of per capita GDP. "Share of informal employment" is the percentage share of informal employment over total employment.

[6] The larger differences among EMDEs likely depend on the fact that this group comprises more heterogenous countries than AEs. Moreover, besides the role of structural policies and other country characteristics, data quality issues might also explain the greater heterogeneity observed for EMDEs. Indeed, as data quality is arguably a stronger issue for EMDEs, measurement error is likely to be more prominent among them. This might also explain the near zero or even positive coefficients estimated for some countries.

[7] Unfortunately, the limited overlap between the employment informality and business start-up cost series prevent us from investigating the association of start-up costs once controlling for the level of informality.

IPUMS DATA AND THE ANALYSIS OF LABOR MARKET STATUS[1]

This chapter describes the Integrated Public Use Microdata Series (IPUMS) International data and associated analyses. These data enable the calculation of detailed summary statistics by employment status across age, gender, and country groups, the estimation of labor market status probabilities at the individual level as a function of core demographics, and the estimation of the association between various structural policies and employment outcomes. In this chapter, we start by describing key features of the data and our cleaning procedures. We then list in detail the samples included in different part of the main analysis and describe how we calculate the aggregate summary statistics reported in the main text. Furthermore, we specify the multinomial probability model used to assess the association between core demographics and employment status, and formally define the counterfactual quantities used to compute gender and age gaps, as well as their decomposition (as presented in the main text). We report additional results obtained from the estimation, omitted from the main text for space reasons, which highlight the heterogeneous associations between demographics and employment status found across countries. Finally, we present the linear probability model used to assess the association between structural policies and characteristics and employment outcomes, as well as some robustness checks. We also present additional results on how the associations vary by skill.

A. IPUMS Data

IPUMS (Integrated Public Use Microdata Series) International is a repository of individual-level national census and other survey data from around the world.[2] Currently, it includes samples from 301 censuses from 85 countries in different years between 1960 and 2015. The vast majority

[1] Prepared by Davide Malacrino.

[2] Minnesota Population Center 2017. IPUMS International underlying dataset sources: Argentina (National Institute of Statistics and Censuses), Armenia (National Statistical Service), Austria (National Bureau of Statistics), Bangladesh (Bureau of Statistics), Belarus (Ministry of Statistics and Analysis), Bolivia (National Institute of Statistics), Botswana (Central Statistics Office), Brazil (Institute of Geography and Statistics), Burkina Faso (National Institute of Statistics and Demography), Cambodia (National Institute of Statistics), Colombia (National Administrative Department of Statistics), Costa Rica (National Institute of Statistics and Censuses), Dominican Republic (National Statistics Office), Ecuador (National Institute of Statistics and Censuses), El Salvador (General Directorate of Statistics and Censuses), Fiji Islands (Bureau of Statistics), France (National Institute of Statistics and Economic Studies), Ghana (Ghana Statistical Services), Hungary (Central Statistical Office), India (Ministry of Statistics and Programme Implementation), Indonesia (Statistics Indonesia), Iran (Statistical Center), Jamaica (Statistical Institute), Kyrgyz Republic (National Statistical Committee), Malawi (National Statistical Office) , Malaysia (Department of Statistics), Mali (National Directorate of Statistics and Informatics), Mexico (National Institute of Statistics, Geography, and Informatics), Nicaragua (National Institute of Statistics and Censuses), Nigeria (National Bureau of Statistics), Panama (Census and Statistics Directorate), Paraguay (General Directorate of Statistics, Surveys, and Censuses), Peru (National Institute of Statistics and Informatics), Portugal (National Institute of Statistics), Romania (National Institute of Statistics), Rwanda (National Institute of Statistics), Spain (national Institute of Statistics), South Africa (Statistics South Africa), Switzerland (federal Statistical Office), Tanzania (National Bureau of Statistics), Trinidad and Tobago (Central Statistical Office), Uganda (Bureau of Statistics), United States (Bureau of the Census), Uruguay (National Institute of Statistics), Venezuela (National Institute of Statistics), Vietnam (General Statistics Office), Zambia (Central Statistical Office).

of samples are 10% samples of the relevant populations (31 out of 47 samples included in our main analysis), although the percentage varies amongst those samples considered from a minimum of 0.04% (India) to a maximum of 33% (France). We select data from 60 countries, for which there are at least two samples after 1990. After our cleaning procedure, described in the next section, we are left with 57 countries with usable information on schooling status (whether an individual is currently in school or not), and employment status. We are also able to establish an individual's labor force status (in/out) and, if in the labor force, whether employed with a salary job, employed without a salary job, or unemployed. When focusing on young people (those aged less than 30), we first classify them as being in school or not and then assign them employment and labor force statuses conditional on not being in school.

B. Data Cleaning

To obtain our final dataset we first encode the raw data using programs provided by IPUMS and then check that the variables of interest are available in the samples. In some cases, we reclassify variables to avoid missing too many observations. We do this checking the data by country year, to avoid "over-imputation". For example, we set missing employment states to "out of the labor force" if the share of missing observations in the country sample is low (e.g. in Argentina this is less than 0.1% of the population). Similarly, since 12% of the observations in the 2007 South Africa sample had missing employment status, we leave the variable "missing" in that year. Other reclassifications include setting the number of children to 0 when the variable is missing, and recoding marital status to only cover three states (never married, currently married/partnered, was married – merging separated/divorcees and widows/widowers). Our cleaning procedure reveals that for some countries there is insufficient information to run the analysis. For example, although China was included in the original selection, the census does not report any information on the employment status. Similarly, Ireland was dropped as it lacked schooling information. Other country samples are dropped at the multinomial logit estimation stage (described later) if the estimation algorithm fails to converge. These steps result in dropping 10 countries. We are then left with 47 countries for the core analysis.

C. Analytical Samples

Different sample groupings are used in different components of the analysis. To generate the cross-sectional statistics, we only use the most recent year for each country. The following samples are included:

- *Sub Saharan Africa*: Botswana 2011, Burkina Faso 2006, Ghana 2010, Malawi 2008, Mali 2009, Nigeria 2009, Rwanda 2002, South Africa 2007, Tanzania 2012, Uganda 2002, Zambia 2010.
- *South and Southeast Asia and Pacific*: Bangladesh 2001, Cambodia 2008, Fiji 2007, India 2009, Indonesia 2010, Malaysia 2000, Vietnam 2009.
- *Latin America and the Caribbean*: Argentina 2001, Bolivia 2001, Brazil 2010, Colombia 2005, Costa Rica 2011, Dominican Republic 2010, Ecuador 2010, El Salvador 2007,

Jamaica 2001, Mexico 2015, Nicaragua 2005, Panama 2010, Paraguay 2002, Peru 2007, Trinidad and Tobago 2011, Uruguay 2006, Venezuela 2001.

- *Emerging Europe, Central Asia, and the Middle East*: Armenia 2011, Belarus 2009, Hungary 2011, Iran 2011, Kyrgyz Republic 2009, Romania 2011.
- *Advanced Economies*: Austria 2011, France 2011, Portugal 2011, Spain 2001, Switzerland 2000, United States 2010.

The size of the samples ranges from 56,025 (Fiji, 2007) to 15 million (Indonesia, 2010). Overall, these data include 41 EMDEs and 6 AEs. This is also the same sample used for the structural policy analysis. While the number of observations varies by specification (due to the selection of different subgroups of individuals, and availability of the relevant policies), the overall number of observations in the dataset is around 90 million (representing approximately 1.8 billion individuals), out of which 72 million are in EMDEs (representing approximately 1.5 billion individuals). Detailed data on the number of observations per specification are available upon request. Some samples included in the analysis date back to the early 2000s. This is a limitation of our analysis, especially when features of the labor market are correlated with structural characteristics and institutions that likely changed over time, albeit slowly in general.

To generate the graphs where statistics are plotted over multiple years, we only select countries for which we have at least two observations. The countries in this sample are: Bangladesh, India, Iran, Mali, Nicaragua, Paraguay, Mexico, Indonesia, Burkina Faso, Nigeria, El Salvador, Fiji, Venezuela, Ecuador, Panama, Peru, Bolivia, Colombia, Zambia, Costa Rica, Malaysia, Malawi, Uganda, Uruguay, Argentina, Brazil, Tanzania, Botswana, Jamaica, Kyrgyz Republic, Armenia, Dominican Republic, South Africa, Trinidad and Tobago, Romania, Ghana, Spain, Vietnam, Cambodia, Switzerland, Rwanda, Belarus, France, Hungary, Portugal, United States.

D. Aggregating Up to Country Age and Gender Profiles

Age and gender profiles reveal striking differences in schooling and labor market outcomes by groups for the average EMDE across geographic regions and vis-à-vis AEs (Figure 3.1). Aggregating up, several patterns emerge for the working age population by geographic region:[3]

a. *15–19-year-olds*: Accounting for 50 percent or more of the age group, schooling is the predominant state across regions and gender, although enrollment is slightly lower for young women than for young men on average in sub-Saharan Africa and South and East Asia and the Pacific. School enrollment for this group is much higher in the average AE though, at over 80 percent. Among those not in school in this age group in EMDEs, the majority of young men are employed, while the majority of young women are either unemployed or out of the labor force (NEET). By contrast, in the average AE, employment accounts for the largest share of those not in school for both young men and women.

[3] The geographic regional groups are roughly aligned with the World Bank regional designations, but only include the EMDEs, while the AEs are considered as a separate group. Due to lack of sufficient regional coverage of the harmonized censuses from IPUMS for the Middle East, the group was merged with Emerging Europe and Central Asia. See Table 1.

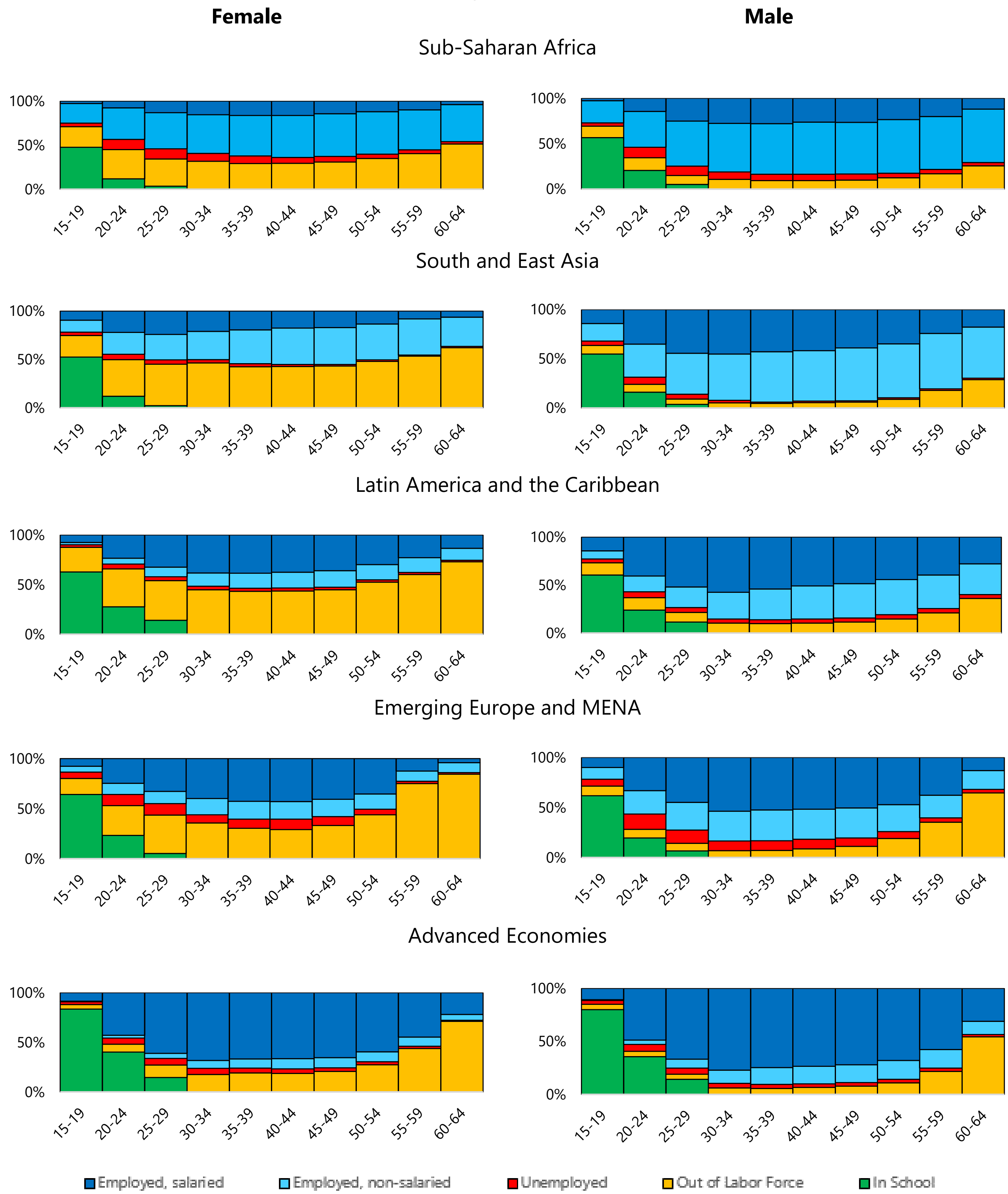
b. *20–24-year-olds*: The share in school in this age group is less than half or even a quarter the share for 15–19-year-olds. The drop is typically larger for young women in the average EMDE. Similar to the 15–19-year-olds that are not in school, and again unlike in AEs, there is a noticeable gender difference visible for the average country across EMDEs, with the majority of young men in the group employed, while young women are more likely to be either unemployed or out of the labor force.
c. *25–29-year-olds*: Apart from Latin America and the Caribbean, the share of this age group in school is generally small, at around 5 percent or less, with no marked differences between young men and women. In the average AE, over 10 percent of the age group are in school. As in the younger age groups, the majority of men not in school in the group for the average country across regions are employed, while the majority of women are not.
d. As also suggested by the macroeconomic data for the working age population, older age groups tend to show a persistent divide between men and women, with men's likelihood of employment higher.
e. Among the employed, there is a large share of jobs that are non-salaried in EMDEs, a common proxy for informality in employment. In the average country in sub-Saharan Africa and South and East Asia, more than half the jobs, either for men or women and at all ages, are non-salaried. In general, there are not large differences in the share of jobs that are non-salaried across age groups, while the share is slightly higher for women than men in the average EMDE. A notable exception though is Latin America and the Caribbean, where men are more likely to have a non-salaried job than women across age groups.

E. Modeling Schooling and Labor Market Status Probabilities

Following much of the literature analyzing labor market outcomes at the individual level, a multinomial logistic probability model is used to assess the roles of individual characteristics (for example, Escudero and Mourelo 2014 for youth labor markets in Kenya). More specifically, to understand the drivers of the observed differences between genders and age groups we estimate binomial and multinomial logistic regressions, modeling the probability of being in school and the probability of being in any employment state as a function of core demographic characteristics widely available at the individual level and harmonized across countries by IPUMS. We model the relevant probabilities as a function of age, educational attainment, marital status, nativity status, dwelling ownership and parental status.[4] To allow for the demographics to have

[4] Specifically: age was modeled as a set of 10 5-year age group dummies (15 to 19, 20 to 24, and so on, through 60 to 64), educational attainment as a set of 4 dummies (less than primary education, completed primary education, completed secondary education, completed tertiary education), marital status as a set of 3 dummies (never married, married, previously married but no longer), nativity as a dummy for being native of the relevant country, dwelling ownership as a dummy for owning the dwelling where the respondent resides, and parental status as a dummy for having at least one own child in the household.

Figure 3.1. Age and Gender Profiles of Schooling and Labor Market Outcomes by Country Group
(percent)

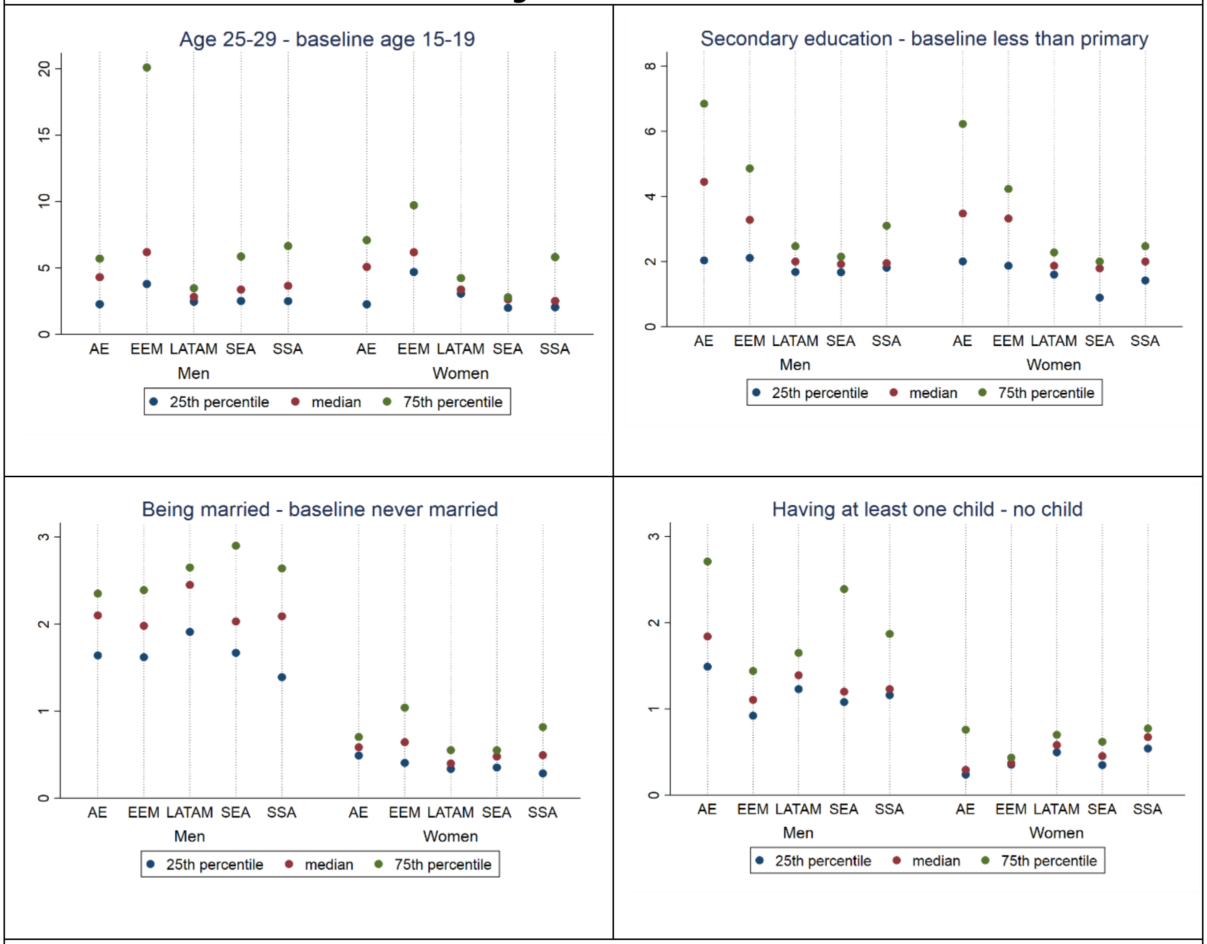


Sources: IPUMS International and IMF staff calculations.
Note: See Table 1 for the country membership of each IPUMS geographic and economy group.

different impacts across country, gender, and age groups, each model is separately estimated for each sample by country, year, gender, and age group (less than 15–29 years old or 30–64 years old) levels. The probability of schooling is only estimated for people aged less than 30 years old and the multinomial logit used to model the employment status probabilities was only estimated for people that are not in school.

The multinomial logit models include four categories: out of the labor force, unemployment, salaried employment, and non-salaried employment. In this appendix, we report the median, 25th and 75th percentile of the distribution of the estimated change in the odds ratio of being employed with a salary job (the exponentiated coefficient) for the different country groups. The baseline state is out of the labor force. We do so for illustrative purposes and more detailed results from the estimation are available upon request. While comparing the magnitude of the coefficients is difficult, the pictures show that the estimated changes in odd ratios vary widely across country groups, and even across countries within group. Figure 3.2 illustrates the distributions of exponentiated coefficients for the salaried employment state for young men and women, while Figure 3.3 shows it for adult men and women. For example, looking at the bottom left panel of Figure 3.2, we can see that the odds of having a salary employment for men who are married in Latin America countries is approximately 2.5 times as large those of non-married men in the median country (LATAM series of dots at the left of the panel, red dot). The odds ratio is only 2 when comparing married to non-married men in South and East Asia and the Pacific (SEA series of dots at the left of the panel, red dot). Looking at women, being married decreases the odds of having a salary job: for example, the odds of having a salary job is approximately half for married women than those for unmarried women in the median Latin American country (LATAM series of dots at the right of the panel, red dot). The distance between dots on the same column reveal differences in the associations between each characteristic and the state even within geographic areas. For instance, looking at Figure 3.3 bottom left panel, among men in Sub-Saharan African countries (SSA series of dots at the left of the panel), being married is linked to an increase in the odds of having a salary jobs that ranges between 10 times (country at the 75th percentile, green dot) to slightly less than 2 times (25th percentile, blue dot).

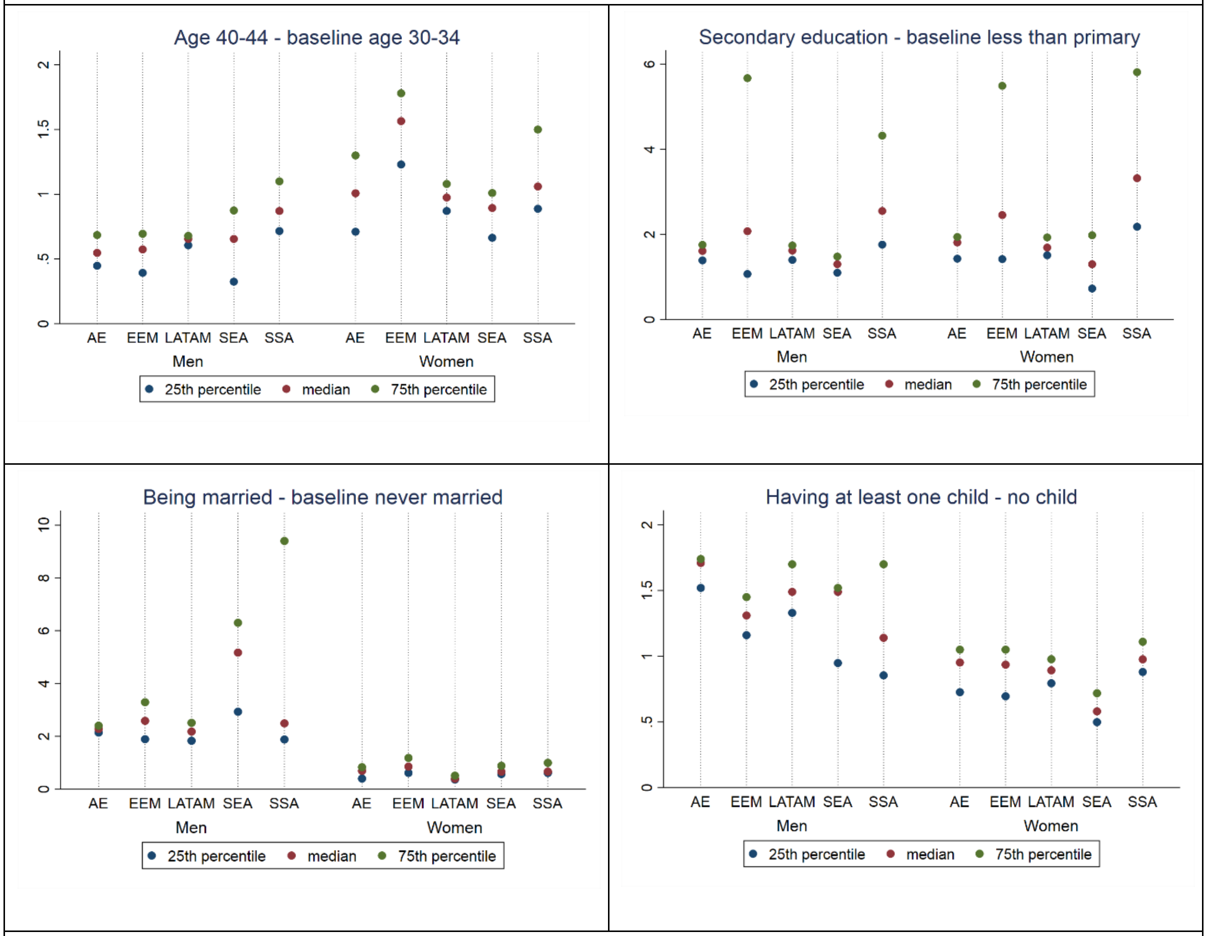
Figure 3.2: Distribution of Exponentiated Coefficients for Salaried Employment State for Young Men and Women



Source: IPUMS International and IMF staff calculations.

Note: The reported exponentiated coefficients are estimated from multinomial logit models estimated at the country, year, age, gender group level for individuals not-in-school. The original model includes 4 states (Salaried employment, Non-salaried employment, Unemployment, and Out of the labor force). All models include age group dummies education controls, a dummy for having at least one child, marital status dummies, nativity status dummy, dwelling ownership dummy. The coefficients shown are for the "salaried employment" state. The baseline state is "out of the labor force". AE is advanced economies, EEM is Emerging Europe, Central Asia, and the Middle East, LATAM is Latin America and the Caribbean, SEA is South and East Asia and the Pacific, and SSA is Sub-Saharan Africa. Each dot in the graph represent the change in odds of having a salary job associated to a change from the baseline to the relevant demographic status in a country. Red dots correspond to the countries with the median odds ratio in their region. E.g. the leftmost dot in the bottom left panel means that in an advanced economy leaving in the median country, the odds that a married young man has a salary job are approximately twice as high as those of an unmarried man. Green dots correspond to the countries whose estimated odds ratio is in the 75th percentile of the distribution, and blue dots to the countries in the 25th percentile of the distribution.

Figure 3.3. Distribution of Exponentiated Coefficients on Salaried Employment State for Adult Men and Women



Source: IPUMS International and IMF staff calculations.
Note: The reported exponentiated coefficients are estimated from multinomial logit models estimated at the country, year, age, gender group level. The original model includes 4 states (Salaried employment, Non-salaried employment, Unemployment, and Out of the labor force). All models include age group dummies education controls, a dummy for having at least one child, marital status dummies, nativity status dummy, dwelling ownership dummy. The coefficients shown are for the "salaried employment" state. The baseline state is "out of the labor force". AE is advanced economies, EEM is Emerging Europe, Central Asia, and the Middle East, LATAM is Latin America and the Caribbean, SEA is South and East Asia and the Pacific, SSA is Sub-Saharan Africa. Each dot in the graph represent the change in odds of having a salary job associated to a change from the baseline to the relevant demographic status in a country. Red dots correspond to the countries with the median odds ratio in their region. E.g. the leftmost dot in the bottom left panel means that in an advanced economy leaving in the median country, the odds that a married young man has a salary job are approximately twice as high as those of an unmarried man. Green dots correspond to the countries whose estimated odds ratio is in the 75th percentile of the distribution, and blue dots to the countries in the 25th percentile of the distribution.

F. Building Counterfactual Labor Market Probabilities

Using the estimated models, we compute counterfactual probabilities for the labor market states by changing the gender and age group for each individual, holding their other characteristics constant. For example, for each woman in the sample we compute her probability of being employed with a salaried job by preserving her observable characteristics but changing the parameters of the model to those estimated from the sample of men in the same age group. More specifically, we obtain the previously described estimated counterfactual probability for women i in country c as follows:

$$\hat{P}^{w,y,c}_{i,\,\mathrm{cf}\;gender}(s = ES|i\;not\;in\;school) = \frac{\exp(X_i^T\hat{\beta}_{ES}^{m,y,c})}{1+\sum_{s\neq ES}\exp\left(X_i^T\hat{\beta}_s^{m,y,c}\right)}$$

while the actual estimated probability for the same individual is estimated as

$$\hat{P}^{w,y,c}_{i}(s = ES|i\;not\;in\;school) = \frac{\exp(X_i^T\hat{\beta}_{ES}^{w,y,c})}{1+\sum_{s\neq ES}\exp\left(X_i^T\hat{\beta}_s^{w,y,c}\right)}$$

where the indices in superscript w, y, c indicate that the probability is computed for women (*w*), who are young (*i*) in country *c*, the subscript index cf stands for counterfactual regarding the indicated variable (here gender), and $s \in \{ES, EN, U\}$, where *s* is the labor market status, *ES* is employed with a salaried job, *EN* is employed with a non-salaried job, *U* is unemployed. The out of the labor force state (*O*; unoccupied) is taken as the baseline state for the estimation and calculated as one minus the sum of the estimated probabilities for the other three states. While $\hat{P}^{w,y,c}_{i}$ is estimated based on the woman's observable characteristics X_i and the coefficients estimated for her group ($\hat{\beta}_s^{w,y,c}$) , the counterfactual probability $\hat{P}^{w,y,c}_{i,cf\;gender}$ is obtained by keeping her observable characteristics X_i fixed, while using the estimated coefficients for the young men in her country ($\hat{\beta}_s^{m,y,c}$). Notice that all parameters are estimated for the three different employment states (*ES*, *EN*, *U*), relative to the baseline state *O* (a result of the rule that the positive probabilities for a set of exhaustive and mutually exclusive events must add up to one).

Similar to the gender swap counterfactual, we can also calculate an age change counterfactual, where the age of each young person in the sample is raised by 15 years and then their probability of being in a certain employment status (for example, unemployed) using the parameters estimated for individuals in the group of people aged more than 30 is computed. More concretely, consider a 20-year-old young woman. The counterfactual probability is:

$$\hat{P}^{w,y,c}_{i,cf\;age}(s = U) = \frac{\exp(X_i^T\hat{\beta}_{U}^{w,a,c})}{1+\sum_{s\neq ES}\exp\left(X_i^T\hat{\beta}_s^{w,a,c}\right)}$$

Where the index a refers to the model estimated for "adults" (aged 30 or more).

The difference between the original estimated probability and the "counterfactual" probability is a measure of the gender/age gap that cannot be explained by the individual-level observable characteristics included in the models. In interpreting the results, it is important to keep two important caveats in mind:

- the validity of the exercise hinges on the assumption that any characteristics/variables omitted play no role in predicting the probability.
- the set of estimated parameters by sample includes a constant that approximately accounts for the average difference between groups not captured by the observables.

In other words, the gap obtained as the difference between counterfactual and actual estimated probabilities ignores possible unobserved heterogeneity that is correlated with the included variables and incorporates both the difference in premiums to observed variables across samples and the average difference across samples as captured by the constants.

As described in the main text, we decompose the "overall gap" in the probability for a given labor market status into components "due to characteristics" and "due to impacts" (as in Figure 3.1 panels 1 and 2):[5]

$$\frac{1}{|M|}\sum_{i\in M}\hat{P}_i^m - \frac{1}{|W|}\sum_{i\in W}\hat{P}_i^w = \left(\frac{1}{|M|}\sum_{i\in M}\hat{P}_i^m - \frac{1}{|W|}\sum_{i\in W}\hat{P}_{i,cf\ gender}^w\right) + \left(\frac{1}{|W|}\sum_{i\in W}\hat{P}_{i,cf\ gender}^w - \frac{1}{|W|}\sum_{i\in W}\hat{P}_i^w\right)$$

$$overall\ gap = (due\ to\ characteristics) + (due\ to\ impacts)$$

since the two members of difference in the first parentheses share the same parameters ($\beta_s^{m,y,c}$), but different observables, while the members of the second difference share the same (here women's) observables but are computed using different parameters. We compute these differences country by country and then average across countries in the same group. Recall that the labor force participation state, conditional on being out of school, is the sum of the probabilities for being employed (salaried and non-salaried) and unemployed.

Results on the NEET state are obtained by computing the individual probability of NEET as

$$\begin{aligned}\hat{P}_i^w(Neet) &= \left(1 - \hat{P}_i^w(in\ school)\right)\left(\hat{P}_i^w(U|not\ in\ school) + \hat{P}_i^w(O|not\ in\ school)\right)\\ &= \hat{P}_i^w(U\ \cap\ not\ in\ school) + \hat{P}_i^w(O\ \cap\ not\ in\ school)\end{aligned}$$

Then we compute country level averages, and further aggregate up at the country group level by taking unweighted averages across the countries in each group.

[5] With slight abuse of notation, we omit the y and c indexes. M and W are the sets of young men a6d women in country c and $|\ \ |$ indicates their cardinality.

In Figure 6 panels 3-4 in the main note, the decennial changes are inferred from the annualized rate of change calculated across the two most recent censuses available in the IPUMS International dataset. For example, if the last two available census years are 2010 and 2008 and the change between the two years is 1%, the 10 years changes is inferred to be 5% (1% times 2/10). More generally, if the distance between the last two available census years is Y, and the estimated change is X%, the ten years change is computed as X%*Y/10. Then, the data point on the x axis of the figures is computed as the share in the earliest of the two available years plus the inferred change.

In Figure 7 panels 5 and 6 in the main note, the gender gap for young women with children is the average gap among young women with children, computed as above. Similarly, the gap for women without children is the average gap for the complementary group. Notice that the position of the overall mean with respect to the averages computed within the two groups of women is informative about the share of women with kids in each country group. The lower the share of women with kids, the closer the overall mean to the mean computed among women without children.

G. Structural Policies and Youth Labor Markets

To estimate the association between macrostructural policies and characteristics and youth labor market outcomes, we estimate the following linear probability model:

$$Y_i = \alpha + \beta Z_{c(i)} + \gamma X_i + \delta W_{c(i),t(i)} + \varepsilon_i$$

where:

- Y_i is the individual i' s outcome of interest (for example, a dummy for being employed).
- $Z_{c(i)}$ is the policy/macroaggregate of interest averaged over time in country $c(i)$.
- X_i is a set of individual i level observable characteristics (the same set included in the estimation of the labor market status probabilities).
- $W_{c(i)t(i)}$ are aggregate controls for country $c(i)$ at time $t(i)$, including real GDP per capita, output gap, time dummies, and country group dummies (the country groups are the usual one defined before). The inclusion of log GDP per capita (PPP) and output gap helps controlling for differences in broad economic conditions across country and differences in the cycle in the year in which the country sample refer to. We also include a cubic time trend in our specification, which helps accounting for the effect of the global cycle at the time of the census of interest.

All regressions include country group dummies, age group dummies, a cubic time trend, log GDP per capita (PPP), and output gap. All regressions, except for those where the gender gap is the dependent variable, also include education controls, a dummy for having at least one child, marital status dummies, nativity status dummy, dwelling ownership dummy. We do not include this set of controls in the gender-gap regression as the estimated probabilities used to compute the gap are mechanically a function of all these variables. To account for broad geographic heterogeneity, we include four country group fixed effects.

In the main note, we report results concerning the employment and labor force participation rates. The first set of results is obtained by defining the outcome variable to be 1 if an individual is employed either with a salaried job or with a non-salaried job. The second set of results is obtained by defining the outcome variable to be 1 if an individual is either employed or unemployed. We also estimated the association of the relevant macroaggregates with the probability of being employed conditional on being a labor market participant, and with our measure of participation gender gap. The former results are obtained by selecting only individuals who are participating and defining the dependent variable to be a dummy for being employed. The latter results are obtained by defining the dependent variable to be the individual-level estimate of the gender gap as described in the previous section.

Individual observations are weighted by the person weights inverse multiplied by the inverse of the total person weights in each county-year sample. This weighting scheme makes our results comparable to simple country level regressions. In other words, each country-year group receives equal weights. We do so to avoid overweighting countries like Indonesia for which we have 7.8 million observations, with respect to Fiji for which we have less than 30,000 observations. This choice is justified by the objective of our analysis, which is to understand how the variation of structural policy indicators and characteristics at the *country level* are associated with youth labor market outcomes.

Standard errors are clustered at the country level, in line with the level of variation of the main variable of interest $Z_{c(i)}$. We only include observations from the most recent year for each country, which precludes the inclusion of country fixed effects (as they would be collinear with the structural policy indicators and characteristics).

Individual-level observables—such as the share of married individuals, educational levels, differences in age structure, differences in education attainment, differences in home ownership and in fertility rates—account for much of the differences across countries. With the individual level data, we can account for this at a much finer level than it is usually possible in standard macro regressions, partly mitigating the consequences of omitting country fixed effects. However, remaining unobserved cross-sectional differences that are correlated with the outcome and the macroaggregate of interest may affect our estimates, which should therefore be interpreted with caution. In addition to the results outlined in the main note, Table 3.1 also reports findings on the probability of employment conditional on participating, and those relative to the gender gap in labor force participation.

As described in the main note, the coefficients estimated for labor force participation are similar to those estimated for the employment rate, while those relative to employment conditional on participation are mostly statistically insignificant. This suggest that most of the effects detected for the employment rate operate through participation, rather than unemployment. The results on the participation gender gap suggest that higher minimum wages, higher EPL (as captured by severance payments), and higher average effective tariff rates are associated with a larger estimated gender gap (more negative), while legal protections for women and (marginally) trade openness are associated with smaller gender gaps (as suggested by the positive coefficients).

In further analysis, we considered whether the same policy has different effects on high versus low skilled segments of the same populations by estimating the following model:

$$Y_i = \alpha + \beta_H Z_{c(i)} \times HighSkilled_i + \beta_L Z_{c(i)} \times LowSkilled_i + \gamma X_i + \delta W_{c(i),t(i)} + \varepsilon_i$$

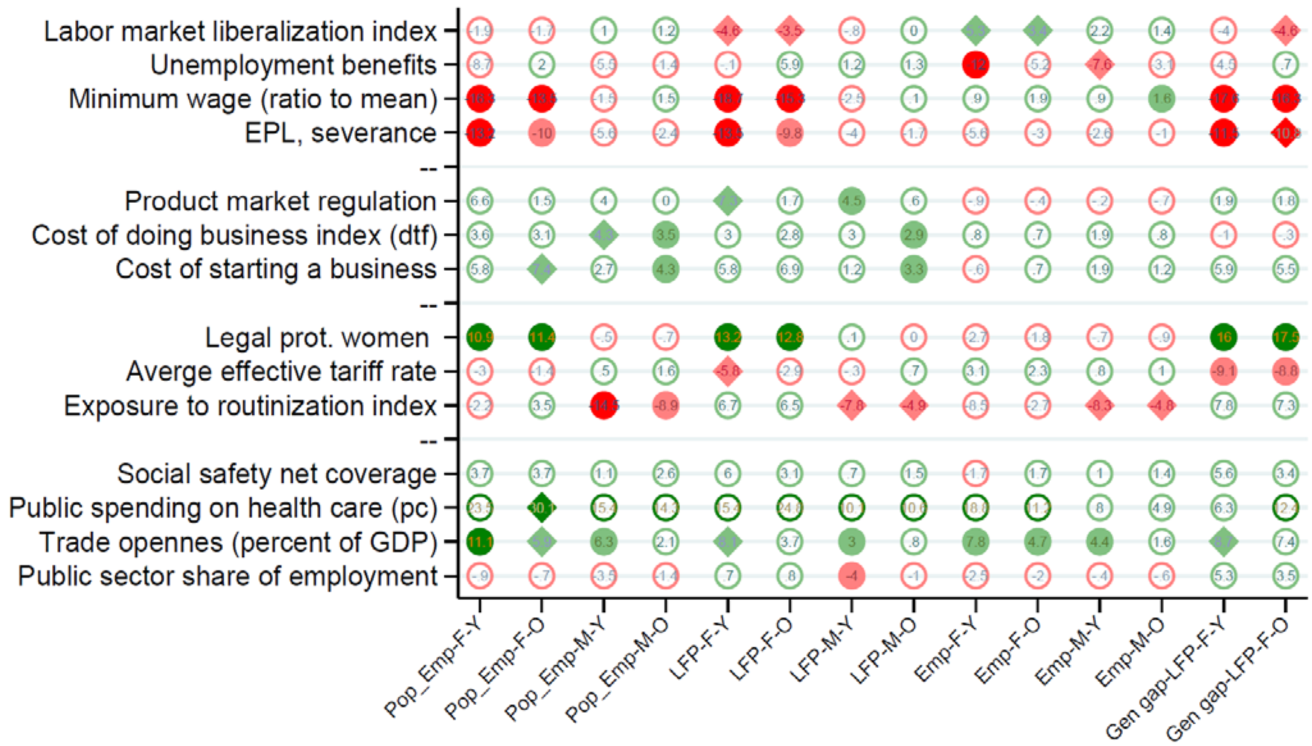
where the interactions are with indicator variables designating "low skilled individuals", those with less than secondary education completed, and "high skilled individuals", those with at least a secondary education degree. When further differentiated between high skill and low skill, the negative association of employment with higher minimum wages is even more strongly evident for young women, with low skill young women more impacted (Figure 3.4). Stricter employment protection's negative association with employment on young women is slightly larger for the high-skilled, but statistically significant for both high and low skill. Such negative associations, while insignificant on average for young men, are also significant for high skill young men.

Finally, we estimated a richer specification in which the coefficients on demographic controls were allowed to vary by country groups. Namely, we estimate the specification:

$$Y_i = \alpha + \beta Z_{c(i)} + \sum_{g \in G} \gamma_g I(c(i) \in g) X_i + \delta W_{c(i),t(i)} + \varepsilon_i$$

where $I(c(i) \in g)$ is an indicator function for country $c(i)$ belonging to group country g, and the groups are "Sub-Saharan Africa", "Emerging Europe, Central Asia, and the Middle East", "Latin America and the Caribbean", and "South and East Asia". Reassuringly, the results are similar to those estimated in our baseline specification and available upon request.

Table 3.1: Regression Results on the Effects of Structural Policies and Characteristics

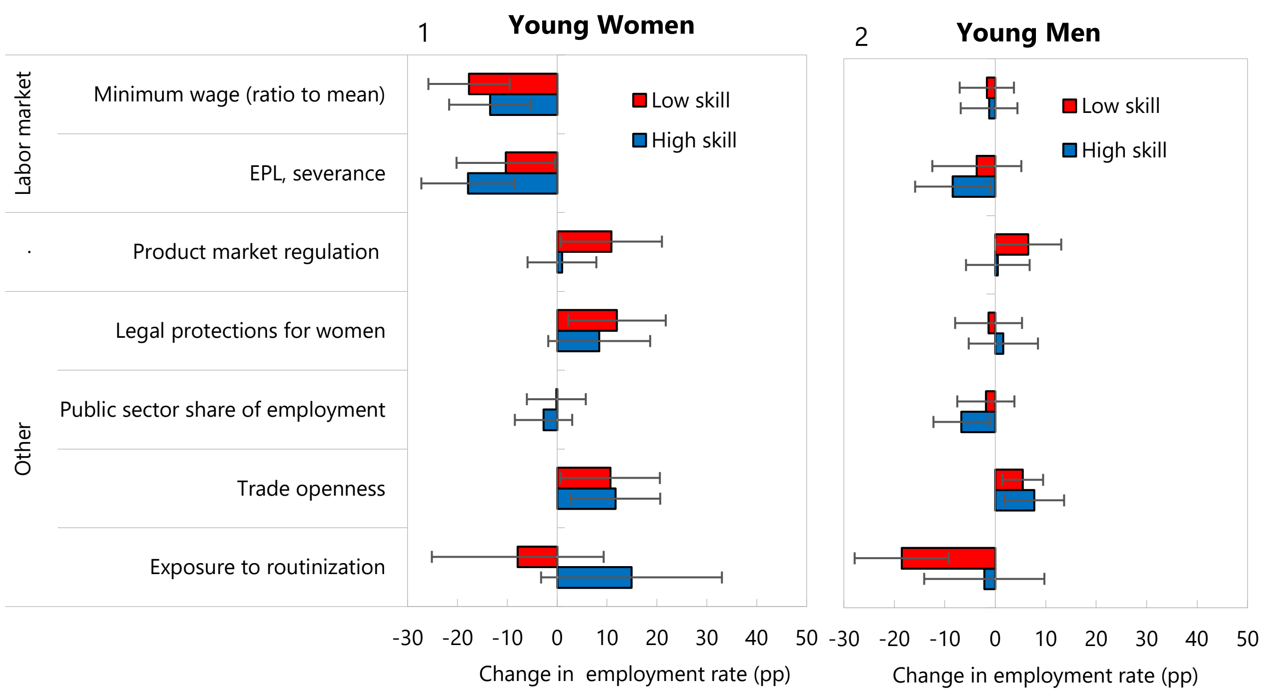


Source: IMF staff calculation on IPUMS. Filled circle p<0.05, Filled diamond p< Hollow circle p>0.10. Numbers are the estimated effects associated with a 25th to 75th percentile change in the indicated row variable.

Note: The regressions are run at the individual level, and weighted as explained in the main text. Standard errors are clustered at the country level. Pop_Emp is the employment rate as a share of the population. The outcome variable is a dummy that takes value 1 if the individual is employed, and all individuals in the relevant sample are included. LFP is labor force participation rate. The outcome variable is a dummy that takes value 1 if the individual is a labor force participant, and all individuals in the relevant sample are included. Emp is employment rate as a share of the labor force. The outcome variable is a dummy that takes value 1 if the individual is employed, and all labor market participants in the relevant sample are included. Gender gap is the variable computed as explained in the main text. F-Y is the sample of women aged 29 or less. F-O is the sample of women aged 30 or more. M-Y is the sample of men aged 29 or less. M-O is the sample of men aged 30 or more. The estimation samples only include EMDEs. All regressions include country group dummies, age group dummies, a cubic time trend, log GDP per capita (PPP) and output gap. All regressions except those with gender gap as a dependent variable also include education controls, a dummy for having at least one child, marital status dummies, nativity status dummy, and a dwelling ownership dummy.

Figure 3.4. Employment Effects of Structural Policies and Characteristics by Skill Level

(25th to 75th percentile change of indicated variable)



Sources: IPUMS International and IMF staff calculations.
Note: Whiskers show the 95 percent confidence interval around the estimates. High skill is completed secondary education or higher, while low skill is less than secondary.

FORMALITY IN YOUTH EMPLOYMENT: ANALYSIS OF THE SCHOOL-TO-WORK TRANSITION SURVEY (SWTS)[1]

With the aim to strengthen the understanding of youth labor market issues and related policies, the ILO School-to-Work Transition Survey (SWTS) of young people between 15 and 29 years old was conducted for 34 countries in two rounds. Survey questionnaires were designed to provide rich information on the youth labor market, comparable to a typical national labor force survey, but harmonized across countries. The first round covered 28 countries between 2012 and 2013, and the second covered 25 countries between 2014 and 2015. From these, we extracted 40 country-year data samples (12 countries in one year and 14 countries in two years; Table 4.1), renaming and recoding question answers as needed to enable cross-country comparative analyses.[2] The total sample is about 35,000 observations.

Among many unique features, the SWTS dataset is particularly useful in studying the formality of youth employment, not least because it allows for the identification of informal versus formal employment at the individual level.[3, 4] We report below some key stylized facts and selected econometric analyses of the potential determinants of employed youth's likelihood of having a formal versus informal job, as discussed in the main note.

At an aggregate level, the youth informality rate—the share of informal employment in total employment—varies substantially across countries, ranging from around 5 percent in Ukraine to around 90 percent in Benin in the sample (Figure 4.1., panel 1). It tends to be lowest among European and Central Asian countries, whereas it is highest in sub-Saharan African countries where the informality share for women also far exceeds that for men (Figure 4.1, panel 2.).

An individual-level logit regression of a binary variable for formal employment—taking the value one for formal employment and zero for informal employment—on demographic characteristics estimated over the SWTS sample of employed youth indicates that: female workers are more likely

[1] Prepared by JaeBin Ahn.

[2] More details on the survey and data files are available at http://www.ilo.org/employment/areas/youth-employment/work-for-youth/WCMS_191853/lang--en/index.htm.

[3] In accordance with the 17th International Conference of Labour Statisticians (ICLS), we define informal employment if one of the followings is met: (i) self-employed in informal enterprises; (ii) contributing family workers and workers for family gain; (iii) members of informal producers' cooperatives; (iv) employees in informal jobs (ILO 2009).

[4] As discussed in the main text, job quality among the employed varies a lot. This is particularly relevant for youth in EMDEs who are more likely to be informally employed (OECD 2015; ILO 2015b). Informal employees and entrepreneurs are typically vulnerable to social and financial risks due to lack of legal and social protection, security of property rights, and the access to benefits (ILO 2002). Lower productivity and earnings in informal jobs also affect economic development and income inequality at the macro level. To the extent that informal jobs tend to be a labor market entry point for youth in EMDEs and can be a stepping stone to a better job, policies to facilitate transition from informal to formal jobs for youth are important.

to work informally than male workers; rural workers tend to have informal jobs more frequently than urban workers; married workers with children are more likely to be informally employed than the unmarried or those without children, which is particularly pronounced for female workers.[5]

The logit analysis further reveals that younger and less educated workers are more likely to be employed in informal jobs.[6] First, the likelihood of informal employment declines with age regardless of education level, suggesting a gradual transition path from early career informal jobs to formal jobs. Moreover, those with secondary or tertiary education are substantially less likely to be informal workers than their peers with primary or no education across all age groups between 15-29. This points to a potential role for general education policy to improve the informal-to-formal job transition among youth. These patterns hold commonly for both male and female youth, although the age effect seems stronger for male youth (Figure 4.1, panels 3 and 4).

Regarding country-level characteristics, policies that foster economic development are expected to reduce informality since the accompanying resource reallocation from primary and traditional sectors towards industry will naturally transform informal sectors to formal. This relationship is suggested by the tight relationship between per capita real GDP and the degree of informality (Figure 4.1, panel 5). However, economic development alone may not be enough to reduce informal jobs in the formal sector, which has more to do with institutions. Consequently, structural policies to lower barriers to formalization in EMDEs—for example, streamlining administrative processes and reducing costs of starting a formal business—may help (Figure 4.1, panel 6).

In order to investigate these issues more precisely, an individual-level linear probability model is estimated for the binary formal/informal employment indicator over the SWTS sample of employed youth. The model includes the individual-level demographic explanatory variables described above, plus variables capturing structural policies and characteristics (introduced one-at-a-time) as well as geographical region fixed effects, country-level log real PPP GDP per capita, and the output gap. The underlying regression results are summarized in Table 4.2, corresponding to Figure 13 and the related discussion in the main note.[7]

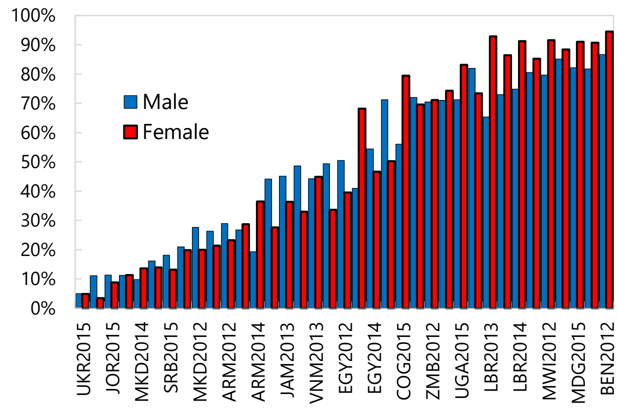
[5] The explanatory variables include: dummy variables for urban area; gender (male/female); having children; ever married; handicapped; age-group/education level categories, as well as country- and year-fixed effects.

[6] These are consistent with earlier findings in O'Higgins, Bausch, and Bonomelli (2017).

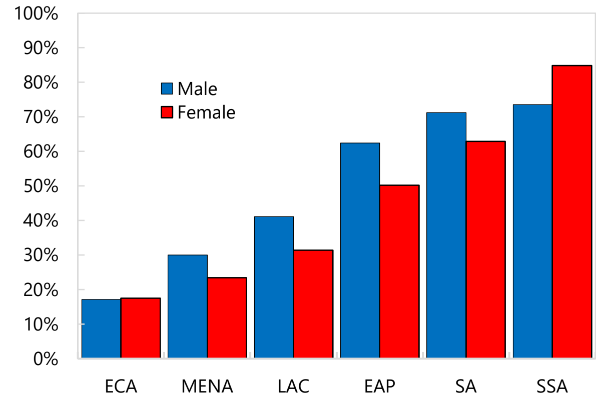
[7] Reported results from the linear probability model estimated by OLS are robust to alternatively using a logit model estimated by maximum likelihood.

Figure 4.1. Informal Youth Employment (SWTS)

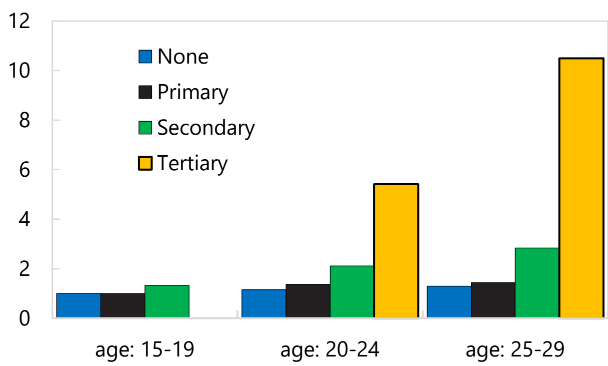
1.Aggregate Informality by Gender across Countries
(in percent of total employment)



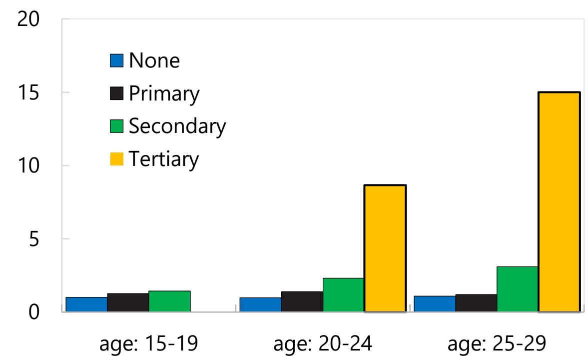
2. Aggregate Informality by Gender across Regions 1/
(in percent of total employment)



3.The Likelihood of Informal Employment for Youth Male 2/
(by education level and age; odds ratio from Logit models)

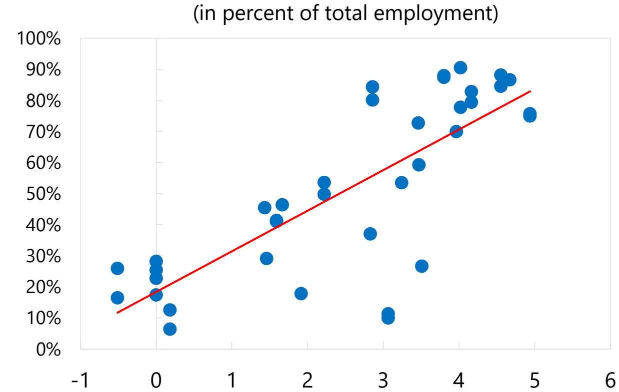


4.The Likelihood of Informal Employment for Youth Female 2/
(by education level and age; odds ratio from Logit models)



5.Informality and Economic Development 3/
(in percent of total employment)

6.Informality and the Cost of Starting Business 3/
(in percent of total employment)



Sources: SWTS, WEO, and IMF staff calculations.

1/ EAP: East Asia & Pacific; ECA: Europe & Central Asia; LAC: Latin America & Caribbean; MENA: Middle East & North Africa; SA: South Asia; SSA: Sub- Saharan Africa.

2/ Odds ratios is expressed as the likelihood of being informal workers for each group relative to those in age 15-19 with no education.

3/ GDP per capita in X-axis is PPP adjusted and in log.

Table 4.1 sample Countries and Years

Country	Year
Armenia	2012;2014
Benin	2012; 2014
Brazil	2013
Cambodia	2012; 2014
Congo, Rep.	2015
Dominican Republic	2015
Egypt	2012; 2014
Jamaica	2013; 2015
Jordan	2012; 2015
Lebanon	2015
Liberia	2013; 2014
Macedonia	2012; 2014
Madagascar	2012; 2015
Malawi	2012
Montenegro	2015
Nepal	2013
Palestine	2013; 2015
Serbia	2015
Slovenia	2014
Tanzania	2015
Togo	2012; 2014
Tunisia	2013
Uganda	2013; 2015
Ukraine	2013; 2015
Vietnam	2013; 2015
Zambia	2012

Table 4.2. SWTS OLS Linear Probability Model—Regression Results

Dependent variable: dummy for formal employment	**(1)** male	**(2)** female	**(3)** male	**(4)** female	**(5)** male	**(6)** female	**(7)** male	**(8)** female	**(9)** male	**(10)** female
1 if 20-24 yrs old	0.079***	0.035***	0.073***	0.055***	0.064***	0.057***	0.081***	0.037***	0.065***	0.035***
	(0.012)	(0.012)	(0.012)	(0.008)	(0.009)	(0.008)	(0.012)	(0.013)	(0.012)	(0.012)
1 if 25-29 yrs old	0.113***	0.059***	0.118***	0.079***	0.111***	0.081***	0.116***	0.063***	0.105***	0.059***
	(0.015)	(0.018)	(0.020)	(0.012)	(0.019)	(0.011)	(0.015)	(0.017)	(0.017)	(0.018)
1 if living in urban area	0.132***	0.104***	0.117***	0.134***	0.105***	0.133***	0.133***	0.107***	0.128***	0.104***
	(0.020)	(0.023)	(0.024)	(0.026)	(0.024)	(0.026)	(0.020)	(0.023)	(0.020)	(0.022)
1 if having children	-0.037**	-0.063***	-0.038	-0.061***	-0.038	-0.061***	-0.038**	-0.065***	-0.038**	-0.063***
	(0.018)	(0.012)	(0.027)	(0.018)	(0.028)	(0.018)	(0.018)	(0.013)	(0.016)	(0.013)
1 if ever married	-0.002	-0.049***	-0.012	-0.065**	-0.004	-0.064**	-0.002	-0.050***	-0.002	-0.049***
	(0.017)	(0.017)	(0.029)	(0.026)	(0.028)	(0.026)	(0.017)	(0.017)	(0.017)	(0.017)
1 if primary education level	0.057	0.018	0.077*	0.048**	0.071**	0.039*	0.056	0.015	0.072***	0.019
	(0.034)	(0.017)	(0.039)	(0.021)	(0.032)	(0.020)	(0.034)	(0.018)	(0.025)	(0.017)
1 if secondary education level	0.128***	0.126***	0.151***	0.134***	0.148***	0.126***	0.126***	0.119***	0.147***	0.127***
	(0.021)	(0.025)	(0.025)	(0.032)	(0.020)	(0.032)	(0.021)	(0.026)	(0.014)	(0.024)
1 if tertiary education level	0.320***	0.355***	0.292***	0.336***	0.293***	0.332***	0.318***	0.348***	0.334***	0.356***
	(0.034)	(0.041)	(0.039)	(0.057)	(0.038)	(0.059)	(0.034)	(0.042)	(0.030)	(0.040)
Output gap	-0.001	-0.006	-0.013	-0.009***	0.005	-0.007	0.000	-0.004	-0.002	-0.006
	(0.007)	(0.004)	(0.010)	(0.002)	(0.011)	(0.004)	(0.007)	(0.003)	(0.006)	(0.004)
per capita GDP in log	0.093**	0.099***	0.194*	0.146***	-0.058	0.103*	0.079	0.076**	0.053*	0.096***
	(0.038)	(0.028)	(0.103)	(0.019)	(0.078)	(0.051)	(0.047)	(0.031)	(0.029)	(0.033)
Labor market regulation index			-0.534***	-0.293**						
			(0.133)	(0.104)						
Product market regulation index					-1.338***	-0.309				
					(0.232)	(0.176)				
Cost of starting a formal business							-0.000	-0.000		
							(0.000)	(0.000)		
Index of legal protections for women									0.297***	0.018
									(0.095)	(0.062)
Year and geographical region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	23,726	19,550	15,256	10,604	15,256	10,604	23,726	19,550	23,726	19,550
R-squared	0.292	0.421	0.285	0.449	0.295	0.448	0.292	0.422	0.300	0.421

Note: This table reports OLS linear probability model with a binary dependent variable that takes 1 if formally employed and 0 if informally employed. All columns include year and geographical region fixed effect. Sample countries included in columns (3) -(6) are: Brazil Dominican Republic, Egypt, Jamaica, Jordan, Madagascar, Nepal, Tanzania, Uganda, Ukraine, Vietnam. Additional countries (Armenia, Benin, Congo Republic, Cambodia, Lebanon, Liberia, Macedonia, Malawi, Serbia, Togo, Zambia) are included in other columns. Robust standard errors clustered at country level are reported in parentheses.

LIFE IN TRANSITION SURVEY: YOUTH PERCEPTIONS AND PERMANENT/TEMPORARY CONTRACTS[1]

This chapter describes the Life in Transition Survey (LiTS) dataset used to analyze the prevalence of permanent versus temporary contracts for employed youth in emerging Europe and central Asia, as well as subjective perceptions related to youth's job search and employment opportunities. It also provides further details regarding the analysis of permanent versus temporary contracts for youth, as well as new results on youth likelihoods of working in the public as opposed to the private sector.

A. Dataset Description

The survey's third round was conducted in 2016 by the European Bank for Reconstruction and Development (EBRD) and the World Bank and covers 24 emerging markets and developing economies (EMDEs), mostly in eastern Europe and central Asia (EECA), as well as a sample of 10 European advanced economies (AEs).2 The survey asks a wide array of questions, including on demographics, economic status, and subjective perceptions and wishes. The representative sample consists of about 1500 respondents per country, including on average about 240 youth (defined here as those between the ages of 18 and 29 as those under 18 were not surveyed), for a total of about 30,000 observations (youth and adults). The following analysis compares youth in EMDEs to youth in AEs, as well as to the working age population (defined here as those between the ages of 30 and 65).

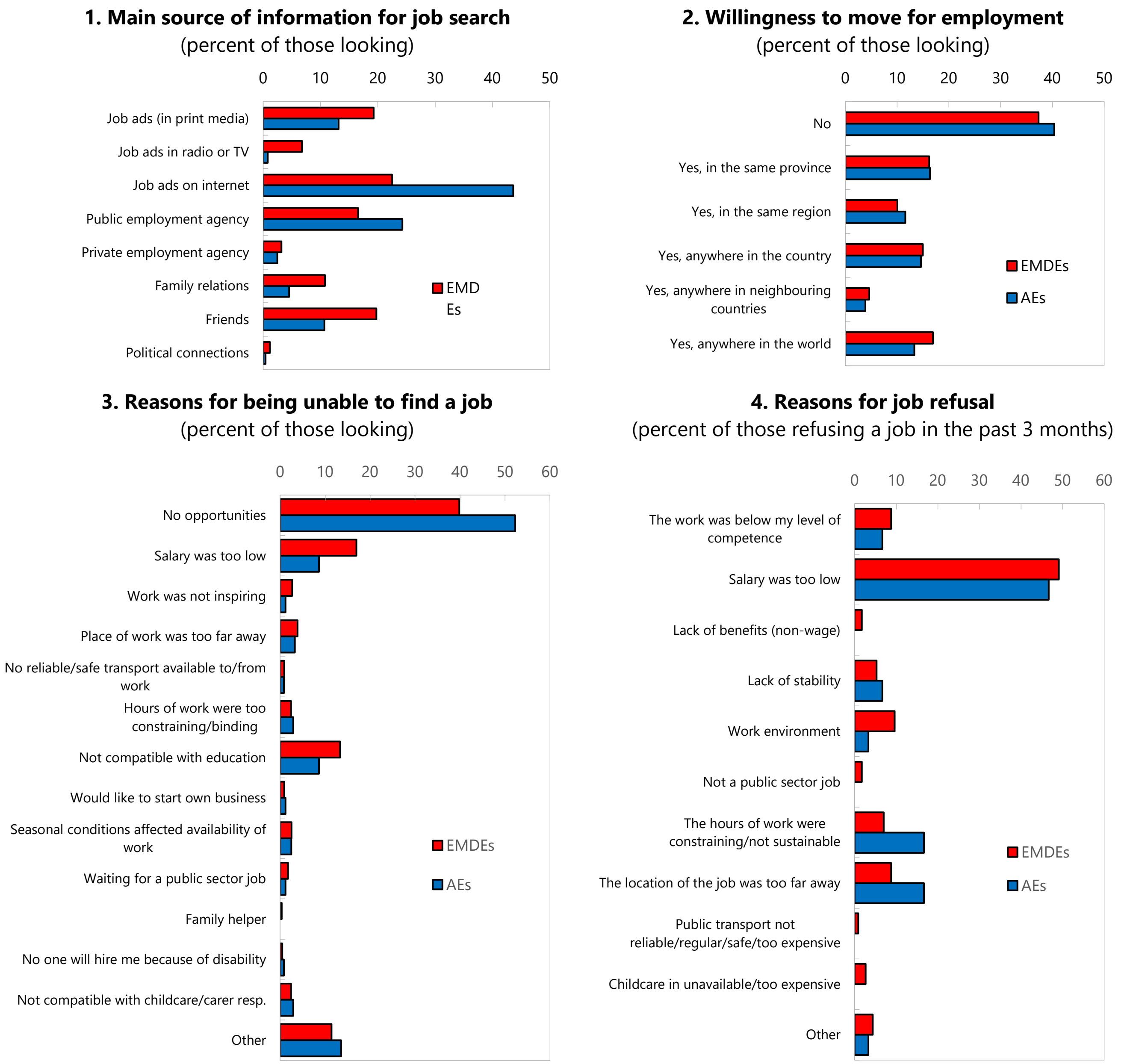
B. Youth Job Search and Subjective Perceptions

Unemployed youth (defined here as those who have not worked at all in the last seven days) in emerging Europe and central Asia are somewhat less likely to be looking for employment than their peers in advanced Europe (24 percent and 32 percent are actively looking, respectively). Excluding those in education, the contrast becomes much more striking: of those not in employment or education only 31 percent are actively looking in the EMDEs in the sample, in contrast with 59 percent in AEs—qualitatively consistent with the IPUMS results presented above.

[1] Prepared by Zsoka Koczan.

[2] AEs include Cyprus, Czech Republic, Germany, Estonia, Greece, Italy, Latvia, Lithuania, Slovak Republic and Slovenia. EMDEs include Albania, Armenia, Azerbaijan, Bulgaria, Bosnia and Herzegovina, Belarus, Croatia, Georgia, Hungary, Kazakhstan, Kyrgyz Republic, Kosovo, FYR of Macedonia Moldova, Mongolia, Montenegro, Poland, Romania, Russia, Serbia, Tajikistan, Turkey, Ukraine and Uzbekistan. For further details see the survey website at https://www.ebrd.com/cs/Satellite?c=Content&cid=1395236498263&d=Mobile&pagename=EBRD%2FContent%2FContentLayout.

Figure 5.1. Employment Search and Perceptions Among Youth in EMDEs and AEs



Sources: Life in Transition Survey III and IMF staff calculations.

Methods of searching for employment also differ systematically between EMDE and AE youth (Figure 5.1). Youth in EMDEs rely more on friends, family, and print media as sources of information on employment opportunities than those in AEs, who overwhelmingly search for job advertisements online and to a lesser extent rely on public employment agencies. There is evidence of age effects in AEs as well as EMDEs: working-age individuals are more likely to rely on public employment agencies and friends, and less on the internet.

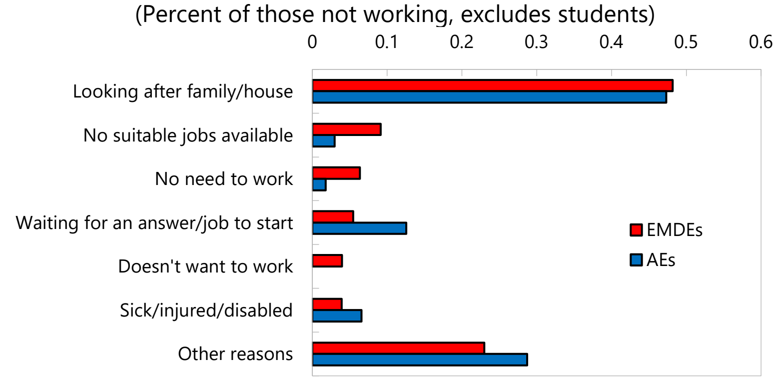
The majority (around two thirds) of youth looking for employment in emerging Europe and central Asia report that they would be willing to move for employment. Among those willing to move, international migration seems most widely favored, with relatively little willingness to move in the same region or to neighboring countries. As might be expected, young are more willing to move than adults, in both EMDEs and AEs (less than half of EMDE adults express a willingness to move).

Most youth report a lack of opportunities as the overwhelming reason for being unable to find a job despite looking for one (40 percent in EMDEs and 52 percent in AEs). This is followed by concerns that salaries are too low (17 percent and 9 percent respectively) and that available opportunities are not compatible with their education (13 percent and 9 percent respectively). Youth in Emerging Markets (EMEs) are more concerned about the lack of opportunities than those in the Low-Income Developing Countries (LIDCs) in the sample, where the main concern is related to salaries.

The share of those reporting that they cannot find a job because it would not be compatible with their childcare/other carer responsibilities is slightly lower in these EMDEs than in AEs, and higher for women than for men. While it is relatively low in comparison to other factors (below 4 percent even for women), such responsibilities are the most important reason why youth do not search for employment (Figure 5.2).

Similar concerns about job prospects can be observed when examining those who refused a job in the past three months (about 12-13 percent of youth in both EMDEs and AEs). In both EMDEs and AEs the primary reason named is because the salary was too low, followed by constraining/ unsuitable hours and too distant location; in EMDEs the work environment was also a concern.

Figure 5.2. Reasons for not Searching for Employment Among Youth in EMDEs and AEs
(Percent of those not working, excludes students)



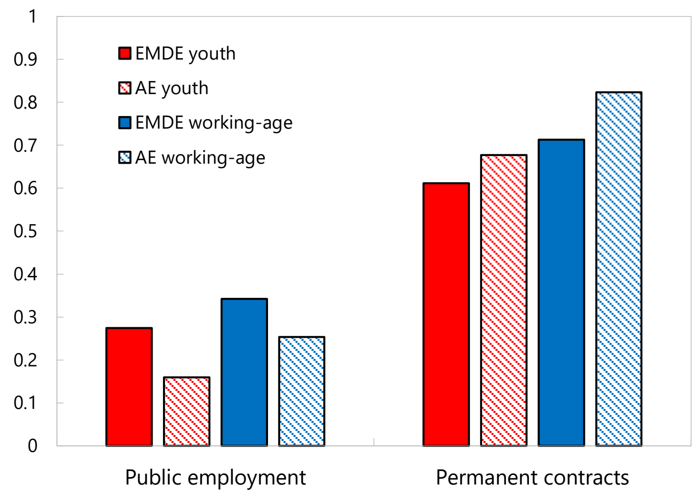
Sources: Life in Transition Survey III and IMF staff calculations.

As noted above, most of those not in employment are not looking because they are in education: 32 percent of those not looking are students in EMDEs, 68 percent in AEs. Excluding those in education, the overwhelming reason for not looking for a job is family responsibilities (48 percent of youth in EMDEs and 47 percent in AEs; Figure 5.2). As above, this is again more prevalent for women. While among youth searching for jobs, lack of opportunities is perceived to be the main reason for not finding employment in EMDEs as well as AEs. In EMDEs, this also appears to discourage youth from looking. 10 percent of youth in EMDEs are not looking for a job because they do not believe there are suitable jobs available, in contrast with only 3 percent in AEs (and this tends to be the case more for men than for women). Youth in AEs are in turn relatively more likely to be waiting to hear about a job, or waiting for a job to start. Reasons for not looking for employment are perhaps surprisingly similar for the young and working age across AEs and EMDEs, with the notable exception of disability being more likely to be a reason for working age men in AEs not looking. While the analysis cannot shed light on what drives this difference, it is consistent with the greater availability of disability support schemes in AEs.

C. Permanent versus Temporary Contracts for Employment and Public versus Private Sector Employment

While the formal-informal employment distinction is important for youth in many EMDEs in other regions, the key distinctions in emerging Europe and central Asia are employment on permanent versus temporary contracts and employment in the public or private sector (public employment constitutes a larger share than in AEs, as expected, for both youth and adults)—see Figure 5.3. Permanent contract refers to having a job on a permanent written contract, as opposed to a permanent job without a written contract, a temporary, seasonal, daily, or other contract. Public employment refers to jobs in the public sector or a state-owned enterprise, while private employment includes jobs at banks, foreign companies, private or international organizations, and self-employment.

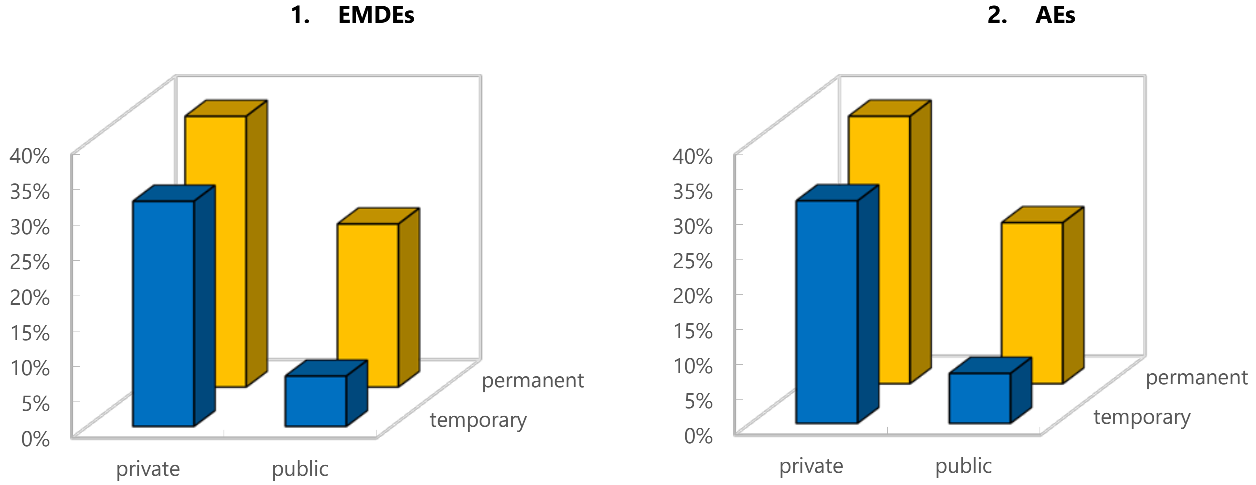
Figure 5.3. Share of Public Employment and Employment on Permanent Contracts
(percent)



Sources: Life in Transition Survey III and IMF staff calculations.
Notes: Public employment refers to having a job in the public sector or a state-owned enterprise as opposed to in a bank, foreign company, private or international organization or being self-employed. Permanent contract refers to having a job with a permanent written contract, as opposed to a permanent job without a written contract, a temporary, seasonal, daily or other contract.

Although these distinctions are not necessarily related (for instance there are permanent contracts in both the public and the private sectors—see Figure 5.4), simple logit models for a binary outcome variable (public/ private or permanent/ temporary, respectively) point to similarities in the effects of household characteristics on public employment and permanent contracts (Table 5.1). Effects are also broadly similar for youth and adults, and across AEs and EMDEs.

Figure 5.4. Shares of Public/private Employment and Employment on Permanent/temporary Contracts Among the Young
(percent)



Sources: Life in Transition Survey III and IMF staff calculations.
Notes: Public employment refers to having a job in the public sector or a state-owned enterprise as opposed to in a bank, foreign company, private or international organization or being self-employed. Permanent contract refers to having a job with a permanent written contract, as opposed to a permanent job without a written contract, a temporary, seasonal, daily or other contract.

The likelihood of being employed in the public sector or of having a permanent contract is higher for older individuals, those who are married, those with higher education, and who own their house., Urban locations are associated with higher likelihoods of having permanent contracts, though may be associated with lower likelihoods of public sector employment. Of course, these should be interpreted as associations rather than causal effects throughout).

Table 5.1. LiTS OLS Linear Probability Model—Regression Results

	Public sector employment								**Permanent contract**							
	Men				**Women**				**Men**				**Women**			
	EMDE young	*AE young*	*EMDE working-age*	*AE working-age*	*EMDE young*	*AE young*	*EMDE working-age*	*AE working-age*	*EMDE young*	*AE young*	*EMDE working-age*	*AE working-age*	*EMDE young*	*AE young*	*EMDE working-age*	*AE working-age*
Age	0.003	-0.001	0.004***	0.002*	0.007	0.006	0.004***	0.006***	-0.002	0.02**	0.003***	0.001	0.01	0.03**	0.002**	0.001
	(0.004)	(0.007)	(0.0006)	(0.001)	(0.005)	(0.004)	(0.0009)	(0.002)	(0.004)	(0.007)	(0.0009)	(0.0008)	(0.006)	(0.009)	(0.0009)	(0.0010)
Married	0.03	0.01	0.04*	0.01	0.03	0.04	0.01	0.04	0.03	0.02	0.06**	0.08***	0.01	-0.01	0.03	0.05*
	(0.03)	(0.03)	(0.02)	(0.009)	(0.03)	(0.05)	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)
Widowed/divorced/separated	0.06	0.04	0.02	0.01	-0.006	0.1**	0.01	0.02	0.04	-0.1	0.01	0.03	-0.05	0.005	0.006	0.03
	(0.05)	(0.1)	(0.02)	(0.03)	(0.04)	(0.05)	(0.03)	(0.02)	(0.06)	(0.1)	(0.03)	(0.02)	(0.05)	(0.08)	(0.02)	(0.02)
Has child	0.008	-0.03	0.001	0.02	0.07**	-0.05	-0.002	0.007	0.02	-0.03	-0.003	-0.02**	-0.009	0.05	-0.003	-0.03
	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)	(0.02)	(0.02)	(0.04)	(0.01)	(0.010)	(0.03)	(0.06)	(0.01)	(0.03)
Lower secondary education	-0.02	0.08**	-0.00002	0.04	-0.10	-0.04	-0.07	0.07	-0.09	0.2	0.1***	0.08*	0.1	0.005	0.09*	0.1
	(0.06)	(0.03)	(0.04)	(0.03)	(0.1)	(0.09)	(0.04)	(0.06)	(0.1)	(0.10)	(0.04)	(0.04)	(0.1)	(0.2)	(0.05)	(0.08)
Upper secondary education	0.07*	0.08**	0.06	0.09***	-0.02	-0.05	0.07	0.1*	0.03	0.2**	0.2***	0.1**	0.1	0.1	0.1***	0.2*
	(0.04)	(0.03)	(0.04)	(0.02)	(0.09)	(0.08)	(0.05)	(0.05)	(0.1)	(0.09)	(0.03)	(0.05)	(0.1)	(0.1)	(0.04)	(0.08)
Tertiary education	0.2***	0.2***	0.2***	0.2***	0.1	0.1	0.3***	0.3***	0.2	0.2	0.3***	0.2**	0.1	0.04	0.2***	0.2*
	(0.05)	(0.03)	(0.05)	(0.02)	(0.10)	(0.1)	(0.05)	(0.05)	(0.1)	(0.1)	(0.03)	(0.05)	(0.1)	(0.1)	(0.04)	(0.09)
Urban	0.003	-0.03	-0.02	0.008	-0.08**	0.03	-0.04**	0.02	0.07	0.07*	0.06***	0.02	-0.008	0.03	0.03*	0.04**
	(0.03)	(0.03)	(0.02)	(0.009)	(0.03)	(0.03)	(0.02)	(0.01)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.06)	(0.01)	(0.01)
Owner	0.03	-0.001	0.04*	0.02	0.010	-0.03	0.04**	0.002	0.07*	-0.02	0.06**	0.07*	0.08**	0.07*	0.09***	0.07*
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.04)	(0.05)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
Number of obs.	1652	588	6699	3233	1473	510	6046	3065	1471	544	5576	2662	1354	477	5348	2729
Adjusted R-squared	0.075	0.033	0.096	0.031	0.090	0.057	0.119	0.106	0.124	0.197	0.157	0.114	0.125	0.180	0.099	0.158

Note: * denotes significant at 10 percent, ** at 5 percent, *** at 1 percent. Regressions also control for log real GDP per capita. Standard errors are clustered at the country level.

YOUTH EMPLOYMENT AND CITY-LEVEL TRADE OPENNESS IN CHINA[1]

There are two main sources for the data underlying the analysis in the box. The Urban Households Survey (UHS) is a representative, household-level survey, conducted annually by China's National Bureau of Statistics. It records a wide range of demographic and socioeconomic information on urban households, including detailed information on income sources, wages, and consumption. Each year, about a third of the sample is reshuffled, such that most households stay in the survey for three years at most. This provides broader cross-sectional coverage in terms of number of households but limits the ability to conduct intertemporal analysis using a true panel. The sample used for the box covers the years 2002 to 2007 before the Great Recession. The individual data for over 200,000 Chinese urban individuals (60,000 urban households) is matched to city-level macroeconomic and trade data for 162 Chinese cities spread across 16 provinces. The city-level data from the CEIC China Database includes GDP, population, exports, and imports at the city-level.

The analysis uses a probit model, with the employment status of individuals that are not in school as the dependent variable:

$$\widehat{P_i^{A,G}}(Y_i = 1 | i\ not\ in\ school) = \Phi\left(X_i^T \widehat{\beta^{A,G}}\right),$$

where Y is a binary variable taking the value 1 if the individual i is employed and 0 otherwise, Φ is the cumulative normal distribution function, β are the linear predictor coefficients for the explanatory variables, and hats indicate estimated quantities. Separate probit models were estimated for each age (denoted by superscript A) and gender (denoted by superscript G) group, allowing for the estimated parameters to differ across men/women and youth/adult. The explanatory variables in the vector X include the key variable of interest—city-level trade openness, defined as the ratio of city-level exports plus imports to city-level GDP—plus a set of controls for individual characteristics (age in years and its square, indicators for the level of educational attainment, marital status, and whether the individual has children), as well as year and province fixed effects.

[1] Prepared by Bin (Grace) Li.

ACTIVE LABOR MARKET POLICIES FOR YOUTH: A BRIEF LITERATURE REVIEW[1]

Active labor market policies (ALMPs) are direct interventions in the labor market that aim to improve the quantity and quality of employment. They may be targeted towards improving outcomes for disadvantaged groups. Drawing upon a number of recent literature surveys and meta-analyses, this section provides an overview of the findings from the literature on the effectiveness of various ALMPs for youth, including vocational training, private sector wage subsidies, public employment, and job search and matching assistance, focusing on lessons for emerging market and developing economies. Overall, the findings on ALMPs for advanced and emerging market and developing economies are broadly consistent (McKenzie 2017; Card, Kluve, and Weber 2018). In general, the evidence is mixed—ALMP effectiveness appears to depend upon the specific context and program design parameters. Moreover, it should be kept in mind that even when deemed effective at the individual level, some ALMPs may still not pass a cost-benefit test, particularly if ALMPs increase youth employment by displacing other workers rather than through the creation of new jobs (Crépon and others 2013). ALMPs may be roughly categorized according to the labor market aspect targeted: supply-side; demand-side; or search and matching interventions (McKenzie 2017).[2] We consider these in turn.

Supply-side ALMPs include vocational training and supplementary education programs that aim to improve the skill set of prospective workers, boosting their productivity and improving their appeal to employers. Such interventions have a long history and were among the most common ALMPs deployed following the global financial crisis (McKenzie and Robalino 2010).[3] However, estimated effects on employment are often modest. Summarizing the findings from a number of randomized experiments on vocational training programs for low income youth, McKenzie (2017) derives an average employment likelihood increase of over 2 percentage points over a 12–18 month time frame for individuals offered training. The average effect on formal employment chances is slightly larger, at over 3 percentage points, suggesting that training programs help shift workers towards more formal jobs. In a meta-analysis of over 800 observational and experimental studies, Card, Kluve, and Weber (2018) find a similar average short-term (less than a year after program completion) effect of training on an individual's employment likelihood, pooling across demographic groups. This average effect triples over time, leading to around 6-7 percentage points employment likelihood increases over 1-2 years and beyond. However, Card, Kluve, and Weber

[1] Prepared by John Bluedorn and Daniela Muhaj.

[2] Other taxonomies have also been used in the literature. For example, Crépon and van den Berg (2016) sort ALMPs according to their primary intention: (i) improvement in the matching process for workers and jobs; (ii) improvement in individual worker productivity; and (iii) improvement in the worker's knowledge about the range of opportunities available and their suitability.

[3] In the case of youth who have dropped out of school, vocational training may act as a substitute for formal education. Such youth-targeted training programs have been particularly common in Latin America, often mixing classroom with on-the-job training (McKenzie 2017).

(2018) also present some evidence that the longer-term effects of ALMPs in general are more muted for youth.

In deciding whether to implement supply-side ALMPs, the positive, but modest, effects of training programs on youth's employment chances must be weighed against both the direct costs, which may vary widely (McKenzie 2017), and indirect costs if targeted group's employment is improved by displacing other workers rather than through new job creation (Fox and Kaul 2017). Moreover, there is ample evidence that specific design choices affect training effectiveness, necessitating their careful consideration. For example, Hirshleifer and others (2016) find larger effects when training is provided privately rather than through government institutes, suggesting that it is important to ensure that training programs are aligned with the private sector's demands.

Demand-side ALMPs include wage subsidies to employment at private firms and public employment programs. If labor costs were fully flexible, then youth or other groups that may have low productivity (due to lack of experience or expertise) should be able to find employment, just at a lower wage. However, as noted by McKenzie (2017), minimum wages, subsistence needs, and hiring and firing costs (whether regulatory or not) may interact with uncertainties about worker productivity to dissuade firms from hiring and workers from accepting. A wage subsidy can offset these costs, improving youth's employment chances, at least while the subsidy is provided. If there are learning-by-doing effects from employment that boost an individual's productivity and make it more transparent to potential employers, then positive employment effects beyond the window of the subsidy exist. Card, Kluve, and Weber (2018) find a positive average employment effect of about 1 percentage point from private subsidies within a year after program completion, pooling across demographic groups. This positive average effect grows with the time horizon, reaching an impressive 20 percentage points after 2 years or more. In a randomized experiment targeting youth in South Africa, Levinsohn and others (2014) found a positive impact on employment chances after 2 years of about 10 percentage points, despite limited actual uptake of the vouchers available to firms. They argue that the positive employment effect may reflect greater search effort by young job seekers who were given vouchers. By contrast, public employment programs have had little or even negative effects on job prospects on average (McKenzie 2017; Card, Kluve, and Weber 2018).

Wage subsidies may also be deployed to help buffer employment against large adverse, temporary shocks, when financially constrained firms might be forced to shed workers that they would otherwise like to keep. For example, in the case of Mexico, Bruhn (2016) found positive employment effects in industries eligible for wage subsidies during the global financial crisis. As McKenzie (2017) notes, this implies that wage subsidies could play an important social protection role against temporary macroeconomic shocks, particularly for youth who have been found to suffer long-lived effects from poor business conditions (see Raaum and Røed 2006, amongst others). As with supply-side ALMPs, program design details for demand-side interventions may impact their effectiveness (for example, whether the subsidy is paid to workers or to employers).

Search and matching ALMPs aim to facilitate the search and matching process of workers and firms aiming to find and fill jobs respectively. They include interventions such as resume preparation aid, labor exchanges, job fairs, and public intermediation programs (connecting firms and prospective employees). Search and matching ALMPs tend to be markedly cheaper than either supply- or demand-side interventions (averaging between one-fiftieth to one-hundredth the per worker cost of vocational training; McKenzie 2017). However, they may also be less effective in countries with high degrees of informality where workers rely heavily on informal networks and other channels to find jobs. McKenzie (2017) notes positive but statistically insignificant effects for eight out of nine randomized experiments of search and matching assistance programs in emerging markets and developing economies, with many oriented towards youth. Fox and Kaul (2017) concur with this broad picture, but also highlight how a program of apprentice-matching in Ghana showed significant and persistent employment effects, suggesting again that local context and program design have large impacts on effectiveness. By contrast, Card, Kluve, and Weber (2018) find a modest and significant positive average employment effect of search and matching ALMPs across a large sample of observational and experimental studies. That said, their meta-analysis indicates that these positive effects do not grow over time, unlike those of supply-side and demand-side ALMPs.

Complementing the traditional ALMPs described above, other interventions focusing on information dissemination and the improved enforcement of labor laws are becoming more prominent (Crépon and van der Berg 2016; McKenzie 2017). These aim to help firms overcome the obstacles they face in innovating and creating jobs, which in part may reflect regulation and labor laws. For example, Bertrand and Crépon (2016) find that teaching South African firms about labor laws and providing legal support to help them deal with these laws led to new jobs.

There is not an overwhelming consensus on the efficacy of ALMPs targeted at youth in emerging market and developing economies. Pooling across a large sample of observational and experimental studies in their review, Card, Kluve, and Weber (2018) conclude that supply-side and demand-side ALMPs with a human capital accumulation component have positive employment effects, but more over the longer term. Focusing more on selected experimental studies, McKenzie (2017) concludes that although estimated employment effects of ALMPs in developing economies are often positive, the evidence is not very robust. He argues that this may indicate that urban labor markets in emerging market and developing economies function more efficiently than commonly thought. Fox and Kaul (2017) review a selection of youth ALMP studies in low income economies, concluding that most ALMPs targeted at formal wage employment for youth are not very effective. Instead, they argue that interventions should focus more on helping youth successfully move to self-employment and informal jobs (including training in social and emotional skills and improved access to finance). That said, there is a broad consensus that ALMPs targeted at youth in emerging market and developing economies should be designed around the country context and specific market failures identified and deployed only after careful cost-benefit analysis (if net benefits are positive).

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