CHAPTER 3

Online Annex

Annex 3.1 Data Sources, Sample Coverage, and Variable Definitions

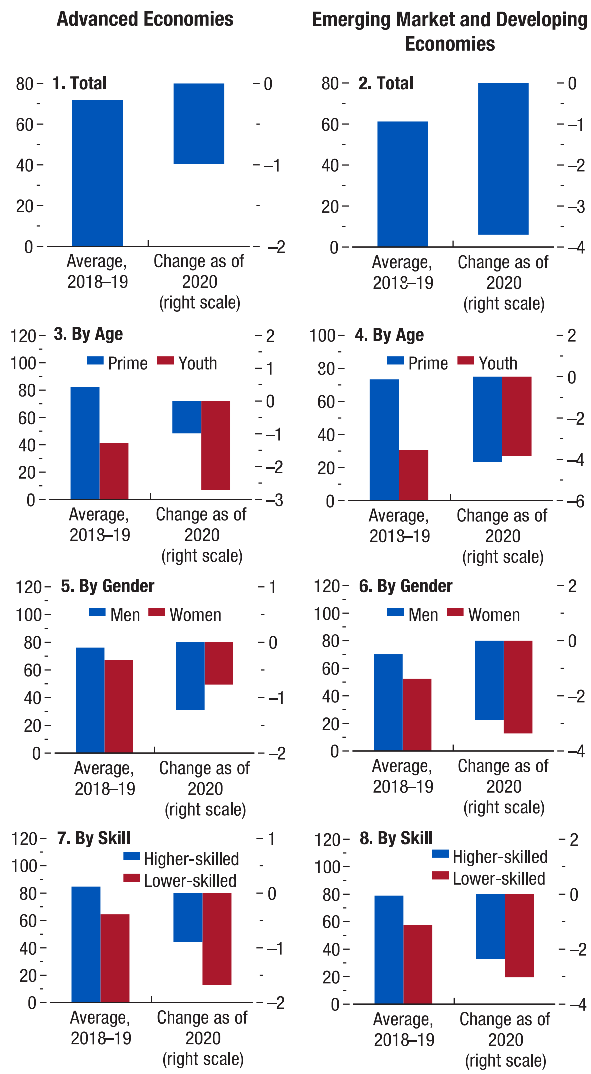
Data sources used in the chapter are listed in Annex Table 3.1.1. Because of data availability at the individual level, the data used throughout the chapter cover mostly advanced economies (AEs). More specifically, the stylized facts section includes both AEs and emerging and developing economies (EMDEs). The sample for the individual-level analysis includes European Union (EU) member countries and the United States. The individual-level EU microdata used in the chapter come from Eurostat: EU Labour Force Survey 1983-2019; and EU Statistics on Income and Living Conditions 2003-2018. The responsibility for all conclusions drawn from the data lies entirely with the authors. The individual-level data for the United States come from IPUMS CPS. The exact samples used varies with the analyses and exercises based on the time coverage and data availability. See Annex Table 3.1.2 for the economies included and the statistical samples where they appear. Annex Table 3.1.3 reports the details of the sectoral classifications used in the chapter.

Business cycle dating is done using the Harding and Pagan (2002) algorithm, which identifies local peaks and troughs that alternate. Since the data are annual, phases are set to have a minimum length of one year. This implies that recessions are defined as contiguous blocks of years with negative real GDP growth. A recovery is defined as either the year directly after a recession or the years after a recession while real GDP remains below its previous historical maximum. Expansion periods are all other years with positive real GDP growth.

Annex Figure 3.1.1 Employment Rates

(Percentage points)

Employment has deteriorated across advanced and emerging market and developing economies, on average.



Sources: International Labour Organization; Organisation for Economic Co-operation and Development; and IMF staff calculations.
Note: "Change" is the average change in the indicated variable across countries in the group, calculated relative to its average value over 2018–19. Higher-skilled = tertiary education and above; Lower-skilled = above secondary and non-tertiary education and below. Prime age = 25 to 54 years old; Youth = 15 to 24 years old. To account for sample coverage changes, the average within the group over time is calculated from the normalized time fixed effects from a regression of the indicated variable on country and time fixed effects (Karabarbounis and Neiman 2014).

Where indicated in the figures, cross-country time averages of series are calculated using the algorithm from Karabarbounis and Neiman (2014) to account for uneven entry and exit of countries in the sample. The algorithm regresses the variable-of-interest on country and time fixed effects, with the initial time period excluded from the time fixed effects. The simple cross-country average in the initial time period is set as the starting value for the average series. Then, the time fixed effects for the relevant period are added to that initial value to recover an estimate of the cross-country average for subsequent times.

Annex Figure 3.1.1 illustrates how employment rates have behaved with the COVID-19 pandemic. This combines the information shown in Figures 3.1 and 3.2 of the main text, since $L = E + U$ (labor force equals sum of employment and unemployment) and $e = (1-u)l$, where $e = \frac{E}{P}$ is the employment rate (employed divided by the relevant population P), $u = \frac{U}{L}$ is the unemployment rate (unemployed divided by the labor force), and $l = \frac{L}{P}$ is the labor force participation rate (labor force divided by the relevant population).

Annex Table 3.1.1 Data Sources

Indicator	Sources
Economy-level employment, unemployment, and labor force participation rates (total and by worker group)	International Labour Organization; OECD Labour Force Statistics
Individual-level labor force survey indicators	European Union Labor Force Survey; European Union Statistics on Income and Living Conditions; IPUMS USA
Stock of job postings	Indeed
Real GDP (level and growth)	IMF, World Economic Outlook database; Haver Analytics; Maddison Project Database
Annual sectoral and total economy employment growth	Choi and others (2018); EU KLEMS; International Labour Organization; OECD Annual National Accounts database; OECD Structural Analysis database; Statistics Canada; US Bureau of Economic Analysis; World KLEMS
Quarterly sectoral employment growth	OECD Quarterly National Accounts database; US Bureau of Economic Analysis
Labor market policy expenditures	OECD Labour Market Programmes database; OECD Demography and Population database

Source: IMF staff compilation.

Annex Table 3.1.2 Sample of Economies included in Analytical Exercises

Exercises	Economies
Labor market conditions in advanced economies (Figure 3.1)	Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Iceland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Labor market conditions in emerging market and developing economies (Figure 3.2)	Argentina*, Brazil*, Bulgaria*, Chile*, Colombia*, Costa Rica*, Croatia*, Ecuador*, Georgia*, Hungary*, Mexico*, Moldova*, Mongolia*, Montenegro, Rep. of.*, North Macedonia*, Peru*, Poland*, Romania*, Serbia*, South Africa*, St. Lucia*, Thailand*, Turkey*, Vietnam*, West Bank and Gaza*
Quarterly Sectoral Employment Growth and Business Cycle (Figure 3.3, panel 1)	Australia (Q1-Q2), Austria, Belgium, Czech Republic, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Korea, Latvia, Lithuania, Luxembourg, Netherlands, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom (Q1-Q3), and United States
Annual Sectoral Employment Growth and Business Cycle (Figure 3.3, panel 2 & 3)	Australia, Austria, Belgium, Canada, Czech Republic, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Netherlands, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, and United States
Sectoral Job Posting (Figure 3.4)	Australia, Austria, Belgium, Brazil*, Canada, France, Germany, Hong Kong SAR, Ireland, Italy, Japan, Mexico*, Netherlands, New Zealand, Poland*, Singapore, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom, United States
Labor Market Turnover across Business Cycles (Figure 3.5) Sectoral Employment by Vulnerability to Automation, Skill Level, and Business Cycle (Figure 3.6) Labor Market Transition Probabilities across Business Cycles and Demographic Groups (Figure 3.7)	Austria, Belgium, Bulgaria*, Croatia*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Greece, Hungary*, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland*, Portugal, Romania*, Slovak Republic, Slovenia Spain, Sweden, Switzerland, United Kingdom, United States
Occupational switch probability on-the-job and via unemployment (Figure 3.8, panels 1 and 3)	Austria, Belgium, Bulgaria*, Croatia*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Greece, Hungary*, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland*, Portugal, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom
Earning changes due to occupational switch, on-the-job and via unemployment (Figure 3.8, panels 2 and 4)	Austria, Belgium, Bulgaria*, Croatia*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Greece, Hungary*, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland*, Portugal, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom
Public Spending on Retention and Reallocation Policies: Before COVID-19 and the Response to COVID-19 (Figure 3.9)	Australia, Austria, Belgium, Bulgaria*, Canada, Croatia*, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary*, Iceland, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland*, Portugal, Romania*, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Effects of job retention and worker reallocation policies (Figure 3.10)	Austria, Belgium, Denmark, Estonia, Finland, France, Italy, Lithuania, Luxembourg, Netherlands, Portugal, Slovenia, Spain, Sweden, United Kingdom

Source: IMF staff compilation.

[1]Asterisk(*) denotes emerging market and developing economies as classified by the October 2020, World Economic Outlook.

Annex Table 3.1.3 Sectoral Classification by Demographic Characteristics Based on Labor Force Surveys, ISIC Rev. 4

Sector code	Sector description	Sector abbreviation	More vulnerable to automation	More lower-skilled	More women	More youth	More high contact-intensive	More teleworkable
A	Agriculture, forestry and fishing	Agri.	√	√				
B	Mining and quarrying	Mining	√	√				
C	Manufacturing	Manuf.	√	√				
D	Electricity, gas, steam and air conditioning supply							
E	Water supply; sewerage, waste management and remediation activities		√	√				
F	Construction	Constr.	√	√		√	√	
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	Trade	√	√		√	√	
H	Transportation and storage	Transport	√	√			√	
I	Accommodation and food service activities	Acc./Food	√	√	√	√	√	
J	Information and communication	Info./Com.				√		√
K	Financial and insurance activities	Fin./Ins.			√			√
L	Real estate activities	Real Est.						N/A
M	Professional, scientific and technical activities							√
N	Administrative and support service activities		√	√				√
O	Public administration and defence; compulsory social security	Public Ad.						
P	Education	Educ.			√		√	√
Q	Human health and social work activities	Health			√		√	√
R	Arts, entertainment and recreation				√	√	√	
S	Other service activities		√		√		√	
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use		√	√	√	√		N/A
U	Activities of extraterritorial organizations and bodies		N/A					N/A
	* More aggregated sectors							
	B, D & E	Min./Ener.	√	√				
	D & E	Utilities	√	√				
	G, H & I	Trade/Acc.	√	√		√	√	
	M & N	Pro. Serv.						√
	O, P & Q	Edu./Heal.			√		√	
	R & S	Arts/Serv.	√		√	√	√	

Source: Carrillo-Tudela and others (2016); EU Labour Force Survey; Integrated Public Use Microdata Series, Current Population Survey; Shibata (forthcoming); and IMF staff calculations.

Annex 3.2 Worker Flows, Trends in Automation, and the Business Cycle

Data Description and Definitions

The dataset used to analyze worker flows is constructed with individual-level, microdata from the European Labour Force Survey (EU-LFS) and the US Current Population Survey (CPS) from IPUMS. The EU-LFS is a repeated cross-section with information about individual labor market status and other variables for the current and previous year. The US-CPS has a panel structure which enables tracking individuals over several periods. The dataset is restricted to working-age individuals aged 16 to 64. To compute worker flow rates by country-year, data from 1979-2020 for the US CPS and 1983-2019 for the EU-LFS are used.[1] To compute worker flow rates by country-sector-year, data are restricted to 2009 onwards to obtain sufficient coverage of sectoral information.

Sectoral information is recoded according to the International Standard Industrial Classification (ISIC) Revision 4 (Rev. 4) classification (see Annex Table 3.1.3). Each ISIC Rev. 4 sector is classified as either "more" or "less" vulnerable to automation. A sector is classified as "more" ("less") vulnerable to automation if more ("less") than 50 percent of workers in the sector (averaged over time by country and then across country averages) belongs to occupations classified as "routine occupations". The definition of "routine occupations" is taken from Carrillo-Tudela and others (2016).[2]

In the constructed dataset dummies are created for the following labor market flows:

1) Hiring
    a. Total hiring: for the EU-LFS, a dummy equal to one if the duration of the individual's current job is less than 12 months. For the US-CPS, the dummy is equal to one if the individual has changed employer at least once over the last year.
    b. Job-to-job hiring, same sector: a dummy equal to one if the hiring dummy is equal to one, and the individual worked in the same sector this and last year.
    c. Job-to-job hiring, different sector: a dummy equal to one if the individual was hired over the last year and is currently in a different sector than one year ago.
    d. Hiring from unemployment: a dummy equal to one if the individual is employed this year and was unemployed a year ago.
    e. Hiring from outside the labor force: a dummy equal to one if the individual is employed this year and was outside the labor force a year ago.
2) Separation
    a. Total separation: a dummy equal to one if:
        i. the individual was hired over the last year and was employed a year ago, or
        ii. the individual is currently non-employed this year and was employed a year ago;

    and zero otherwise.

---

[1] Time coverage varies across the countries in the EU-LFS.

[2] Occupations from the ISCO-08 occupational classification scheme categorized as Routine are: Clerical Support Workers; Services and Sales Workers; Skilled Agricultural, Forestry and Fishery Workers; Craft and Related Trade Workers; Plant and Machine Operators; and Assemblers, Elementary Occupations, and Armed Forces occupations. Non-Routine occupations are: Managers; Professionals; and Technicians and Associate Professionals.

b. Separation to unemployment: a dummy equal to one if the individual was employed last year but unemployed this year, and zero otherwise.
c. Separation to outside the labor force: a dummy equal to one if the individual was employed a year ago but outside the labor force this year, and zero otherwise.

Aggregation

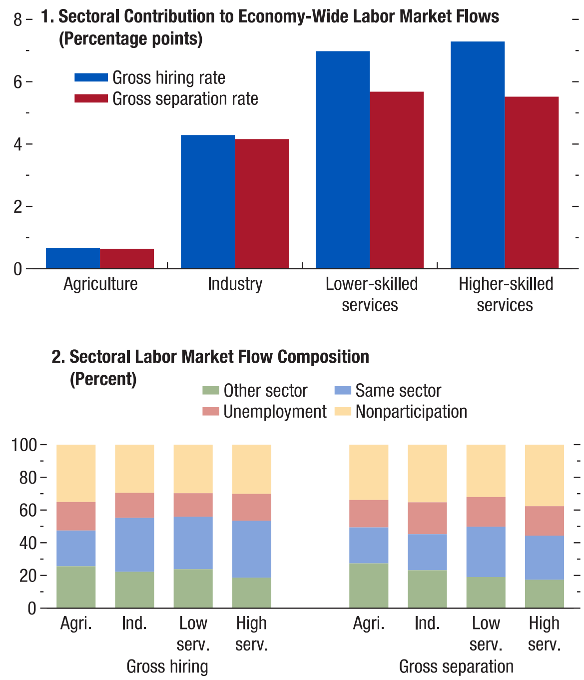
Aggregate flow measures by country-year are created by weighted sums of the underlying dummies (Annex Figure 3.2.1). The survey weights are rescaled such that they sum to unity for each country-year cell.[3]

Aggregate measures by country-sector-year are also created by weighted sums of the underlying dummies for each country, sector, and year combination. As for the economy wide measures, the weights are rescaled to sum to unity for each country-year cell. To correct for missing values, the same restrictions as for the economy wide data is applied.[4]

Adjustments to the data by country-year are made to ensure consistency. First, the sum of (i) job-to-job hiring, (ii) hiring from unemployment, and (iii) hiring from outside the labor force are adjusted such that the components sum to total hiring (scaled uniformly to ensure constant composition). Second, the sum of (i) job-to-job hiring within sector, and (ii) job-to-job hiring between sector are adjusted such that the components sum to total job-to-job hiring (scaled uniformly to ensure constant composition). Third, the sum of (i) separations to outside the labor force, (ii) separations to unemployment, and (iii) job-to-job separations are adjusted such that the

Annex Figure 3.2.1. Sectoral Labor Market Flows and Composition

Gross hiring varies across sectors, and job-to-job and job-to/from-joblessness flows account for roughly equal shares of gross flows.



Sources: EU Labour Force Survey; Integrated Public Use Microdata Series, Current Population Survey; and IMF staff calculations.
Note: Hiring and separation rates and their components are calculated as annual hires/separations divided by the average employment over the current and previous year. Bars show average rates or composition of flows by type over countries and years (2009–19) in the selected sample across sectors. Service sectors are classified as lower-skilled based on whether the share of lower-skilled workers is above the economy-wide average. Industry comprises mining, manufacturing, utilities, water and sewage, and construction sectors. Rates for the aggregated sectors are calculated as the sum of underlying sectors averaged over countries. Agri. = Agriculture; High serv. = Higher-skilled services; Ind. = Industry; Low serv. = Lower-skilled services.

[3] Missing values are removed as follows: For *employment, total hiring*, and *total separations*, only observations with non-missing values for labor market status in the current year are kept. For *job-to-job hiring, unemployment-to-job hiring,* and *non-participation-to-job hiring* only observations with non-missing values for current labor market status and last year are kept. *For job-to-job hiring, same sector* and *job-to-job hiring, other sector* only observations with information on labor market and sector for the current and last year are kept. For *total separations*, only observations with non-missing values for labor market status are kept.

[4] In addition, the following restrictions are used: For *employment*, *total hiring*, *job-to-job hiring, unemployment-to-job hiring,* and *non-participation-to-job hiring* only observations with non-missing observations for current year sector are kept. For *total separations, separations to unemployment,* and *separations to non-participation* only observations with non-missing observations for sector last year are kept. For *employment*, *total hiring*, *job-to-job hiring, unemployment-to-job hiring,* and *non-participation-to-job hiring* the sector is assigned using the individual's current year sector. For *total separation*, *separation to unemployment*, and *separation to non-participation* sector is assigned based on the individual's sector last year.

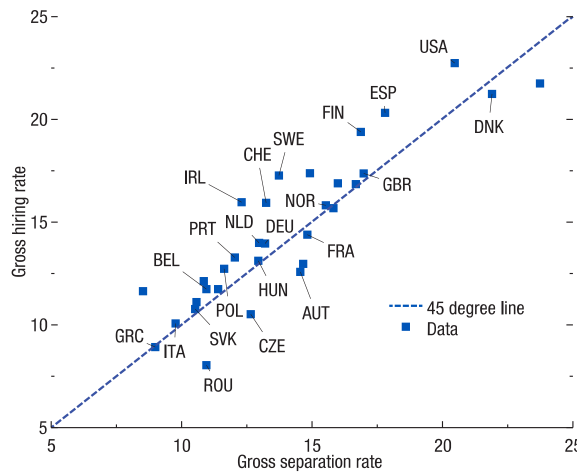
components sum to total separations (scaled uniformly to ensure constant composition).[5]

Adjustments to the data by country-sector-year are also made to ensure consistency across flow measures. In addition to the adjustments made in the data by country-year, the following adjustments are also made: first, the sector-by-sector separations to other sectors are adjusted such that they sum to hires to other sectors economy wide. This is because a sector-to-sector hire must imply a sector-to-sector separation elsewhere and *vice versa*. Second, same sector separations are equalized to same sector hires for each country-sector-year. This is because within a given sector separation must imply a same sector hire.

All flows are expressed as percent of average employment over the current and last year (see Annex Figure 3.2.2).

Annex Figure 3.2.2. Labor Market Turnover across Countries
(Percent)

Gross hiring and separation rates vary markedly across countries.



Sources: EU Labour Force Survey; Integrated Public Use Microdata Series, Current Population Survey; and IMF staff calculations.
Note: Hiring and separation rates are calculated as annual hires/separations divided by the average employment over the current and previous year.

Variation of Flows over the Business Cycle

To assess how flow rates vary over the business cycle the following regression is run:

$$flowrate_{ct} = \alpha + \lambda_c + \beta Recession_{ct} + \phi Recovery_{ct} + \varepsilon_{ict}$$

where $flowrate_{ct}$ is the relevant hiring or separation rate in country *c* at time *t*. λ_c are country fixed effects. $Recession_{ct}$ and $Recoveries_{ct}$ are dummies for recession and recovery periods (see online annex 3.1). As such, they capture deviations from expansion periods, which is the excluded category. Standard errors are clustered at the country-level. The average country fixed effect plus the constant α thus measures the average level for the relevant flow rate during an expansion. Adding the βcoefficient to this yields the average level during a recession, while adding the ϕ coefficient yields the average level during a recovery (see main text Figure 3.5).

[5] Notice that only (i) separations to outside the labor force, and (ii) separations to unemployment are adjusted as (iii) job-to-job separations are set equal to job-to-job hires (defined above).

Annex 3.3 Individual Labor Market Experiences: Transition Probabilities and Earnings Changes

Data Description and Labor Market Transitions Definitions

This section describes the data structure and the outcomes used for the individual level analysis. The EU-LFS and the European Union Statistics on Income and Living Conditions (EU-SILC) survey are the sources of the individual level data. For a description of the EU-LFS repeated cross-section see Section 3.2. The EU-SILC data are instead aggregated as follows: first, to obtain a comprehensive dataset for each country-year, four EU-SILC data files (household register, household data, personal register, personal data) are merged. Second, observations are appended to have a panel of individuals for each country. To avoid duplicate personal indicators (PIDs), the sample is restricted to individuals who appear for 4 years consecutively in the survey.[1] Following Nekarda (2009), the matching validity for all PIDs is computed, considering whether the sex is the same and the age difference between two consecutive years is within ±0.5 years for the same PIDs. Lastly, the unmatched persons are eliminated from the panel, and weights are readjusted to have the same aggregate cross-sectional weights.

The empirical analysis of labor market transitions and policy effects considers the following outcome of interests:

1) Job finding: a dummy equal to one for individuals that were unemployed last year and found a job this year, and zero otherwise.
2) Separation: a dummy equal to one for those that, conditional on being employed last year, do not have a job this year, and zero otherwise.
3) Sectoral transitions: a dummy equal to one if an individual, conditional on being employed this and last year, changed sector of employment this year, and zero otherwise. One-digit sectors are defined according to the ISIC Rev. 4 classification (see online annex 3.1).
4) Occupational switches:[2] To measure the extent of occupational switches, the analysis follows Carrillo-Tudela and others (2016) and considers occupational switches with and without non-employment spells. The probability of occupational switching is defined by considering (i) employment-to-employment (EE) or "on-the-job" transitions, and (ii) unemployment-to-employment (UE) or "via unemployment" transitions. More specifically:
    a. On-the-job occupational switch: a dummy equal to one if an individual, conditional on being employed this and last year, changed occupations, and zero otherwise.

[1] In the case of France, 4-year restrictions are not imposed since the survey is designed to be a 9-year panel.

[2] Occupation categories are based on the International Standard Classification of Occupations one-digit scheme, version 2008 (ISCO-08): 1. Managers; 2. Professionals; 3 Technicians and Associate Professionals; 4 Clerical Support Workers; 5 Services and Sales Workers; 6 Skilled Agricultural, Forestry and Fishery Workers; 7 Craft and Related Trades Workers; 8 Plant and Machine Operators and Assemblers; 9 Elementary Occupations. Armed forces occupations (defined as 0) is excluded from the sample.

b. Via unemployment occupational switch: a dummy equal to one if an individual, conditional on being unemployed last year and employed this year, changed occupation this year, and zero otherwise.

5) Earnings changes are defined as the log change in real earnings (nominal earnings deflated by the consumer price index) as follows:

$$dlnEarning_t = 100 * (\ln(Earning_t) - \ln(Earning_{t-l}))$$

Earnings changes are defined over a two-year period for "on-the-job" occupational switches among those who continue to be employed, and over three years (change of earning between this year and two years ago) for "via unemployment" for those who were employed two years ago, unemployed last year, and employed this year.

Empirical Strategy to Estimate Labor Market Transitions

This sub-section provides technical details about the estimation of the labor market transitions presented in the chapter. To estimate the likelihoods of job finding, separation and job-to-job transitions at the individual level a set of linear probability models are estimated.

First, to document how labor market transitions vary with the business cycle the following model is estimated:

$$outcome_{ict} = \alpha + \lambda_c + \tau_t + \beta Recession_{ct} + \phi Recovery_{ct} + \varepsilon_{ict},$$

where the outcome variable is one of the labor market transitions for individual *i* in country *c* at time *t*. The estimations are restricted to working-age population individuals only. The regression is also weighted using the individual-level weights rescaled to sum to one for each country-year.[3] This ensures that each country-year observation is equally weighted in the estimation. Standard errors are clustered at the country-year level.

$Recession_{ct}$ and $Recovery_{ct}$ are dummies for recession and recovery periods as described in online annex 3.1 and capture the deviation from expansion periods. The coefficient on the constant α measures the average labor market transition during expansions (the excluded category).[4] λ_c and τ_t are country and year fixed effects respectively. Figure 3.7 in the main text reports the average transitions during each business cycle phase together with the 95 percent confidence interval.[5]

To study the effect of individual-level demographic and socioeconomic characteristics on the probability of experiencing a certain labor market transitions the following model is estimated:

$$outcome_{ict} = \gamma_{ct} + \beta X_{ict} + \varepsilon_{ict}$$

---

[3] In the case of the EU-SILC data the longitudinal sampling weights provided by the EU-SILC are used.

[4] Since the regression includes country and year fixed effects, to obtain the average during expansion periods the averages of the country and year fixed effects are added to the constant.

[5] The average transitions in recessions and expansions are given by $\alpha + \beta$ and $\alpha + \phi$, respectively.

Where X_{ict} is a vector of individual-level and socioeconomic characteristics including age, gender, marital status, and skill level (as captured by educational attainment). More specifically the following dummy variables are defined: $youth_{ict}$ is equal to one for individuals between 15 and 29 years of age, old_{ict} is equal to one for those aged 55 to 64, $lowskill_{ict}$ is equal to one for those with non-tertiary and secondary education and below, $married_{ict}$ is equal to one for married individuals, $female_{ict}$ is equal to one for women.[6] The base category is prime-age, unmarried, high-skilled men. γ_{ct} are country-year fixed effects that control for any potentially time-varying macroeconomic factors (including policies and business cycle drivers).

The previous model is then extended to study how the effects of the business cycle vary with individual level characteristics as follows:

$$outcome_{ict} = \gamma_{ct} + \beta X_{ict} + \theta X_{ict} * Recession_{ct} + \lambda X_{ict} * Recoveries_{ct} + \varepsilon_{ict},$$

where θ and λ measure the deviation during recessions and expansion from the base category in expansions.[7] The discussion of the analysis focuses on youth, the lower-skilled, and women.

Job Finding, Separation, and Sectoral Employment Switches

The aggregate probability of finding a job is 30 percent on average in our sample, whereas separation and sectoral switches are both around 3 percent. Figure 3.7 in the main text shows that findings at the individual level are lower in recessions and recoveries with respect to expansions. Whereas separations appear to be always higher with respect to expansions. Sectoral switches are procyclical as found in the literature (Murphy and Topel 1987; Carrillo-Tudela and others 2014; Carrillo-Tudela and Visschers 2014; Carrillo-Tudela and others 2016), but the effect is not statistically significant.

Unpacking the transition likelihood observed before reveals a certain degree of heterogeneity across individual level characteristics and also that the impact of recession is particularly adverse for specific demographic groups. As shown in Figure 3.7 in the main text on average finding a job is easier for the young, but more difficult for women and those that are low skilled. For separations there are no striking differences across categories. And for sectoral switches we observe that the young are again the most advantaged category.

When zooming in on past recovery periods, as shown in Figure 3.7 in the main text for recession periods, it appears that the young are particularly disadvantaged in finding a job, while women tend to be less likely to be laid off . The lower-skilled tend instead to have both a higher likelihood of finding a job and also of losing it. There is no clear pattern in the sectoral transitions.

---

[6] The regressions based on the EU-LFS data includes these extra set of dummies: $national_{ict}$ which is equal to one for national of country *c*, and $child_{ict}$ which is equal to one for individuals with children. In the US-CPS and the EUSILC data youth is a dummy equal to one for those aged 16 to 29.

[7] The country-year fixed effects absorb the dummies for recessions and recoveries.

Occupational Switches and Earnings Changes Results

Figure 3.8 in the main text shows the probability of occupational switches and their earning consequences. As discussed in the main text, the probability of switching occupation is much higher via unemployment (at close to 50 percent) than on-the-job (at around 12 percent). While on-the-job reallocation is associated with an earning gain of about 2 percent, an occupational change via unemployment is associated with a large earning penalty of about 15 percent. These findings are broadly in line with the literature (Huckfeldt 2018 and Gertler and others 2020).[8] Turning to individual level characteristics, the results suggest that: (i) occupational switches are less likely for women relative to men both on-the-job or via unemployment; (ii) however, once women switch occupations, the earnings gain from on-the-job switches or penalties via-unemployment is larger for women than men on average; (iii) youth are more likely to switch both on-the-job and via unemployment, and they experience larger gains in earnings relative to prime-age individuals; and (iv) the findings do not suggest any statistically significant difference between lower-skilled and higher-skilled individuals, when comparing recessions to expansions. However, the occupational switch probability via unemployment increases more for lower-skilled workers during recessions, potentially implying distributional consequences for lower-skilled workers.

This section considers several different margins that were not discussed in the main chapter due to space constraints:

(i) Non-participation

Individuals who switch occupation via non-participation are similar to those who go through an unemployment spell. The earnings penalty for those going through non-participation that switch occupations is not statistically significantly different from zero. The sample size for the non-participation spell is much smaller than for those who experience an unemployment spell. Given that the COVID-19 recession has also affected workers strongly attached to the labor force, the earnings penalty for those going through an unemployment spell is more relevant for the current conjuncture.[9]

(ii) Hourly wage changes

The results for earnings gain/loss in the main text are primarily due to changes in hourly wages and not to changes in hours worked. When considering hourly wages instead of earnings, the hourly wage penalty due to an occupational switch via unemployment is estimated to be equal to −14.8 percent.

(iii) Duration of unemployment

[8] These results in the main text are qualitatively in line with the literature, however it is not possible to precisely compare the magnitudes of this measure in the literature due to differences in sample of countries and level of disaggregation of occupation categories.

[9] Some suggestive evidence of stronger labor market attachment among the unemployed pool could be implied by the high share of unemployed persons who are on "temporary layoffs" during the COVID-19 crisis, who historically had a higher chance of finding a job and getting recalled to their previous employers. See for instance, Shibata (forthcoming), for discussions on the much higher share of unemployed persons on temporary layoff during the COVID-19 recession than the Global Financial Crisis in the US labor market.

It is important to note that the earnings penalty could be a function of the duration of the unemployment spell before reemployment. The baseline specification for earnings changes considers individuals going through a one-year unemployment spell. When extending the analysis considering all the possible years under unemployment in the EU-SILC dataset (up to 7 years of for France and 2 years for all the other countries), the earnings penalty for the workers that experience unemployment is estimated to be 19 percent, higher than the value under the baseline specification. This suggests a potentially stronger earnings penalty for workers with longer unemployment spells.

(iv) Selection

While the results in main text have shown that on-the-job occupational switches are associated with an earnings gain and those via unemployment are associated with an earnings penalty, it could be due to selection (and unobserved heterogeneity). For instance, workers who have a higher ability select themselves into switching occupations on-the-job. If so, earnings gains for switchers relative to stayers are observed because those who switch have higher ability, not because they switched occupations. While individual fixed effects cannot be included as multiple occupational switches are not observed per individual due to the shorter longitudinal dimension of the panel, the inclusion of pre-displacement earnings in the regression analysis could control some aspects of the unobserved heterogeneity. Even after controlling for pre-displacement earnings, on-the-job occupational switches are still associated with an earning gain of 1.53 percent while that via unemployment is associated with an earnings penalty of –16.9 percent.

Policy Analysis

The empirical framework highlighted in the previous section is extended to study the role of policies. More specifically, the analysis focuses on two policies that are particularly relevant for the current conjuncture: workers' reallocation and job retention policies.

$$outcome_{ict} = \alpha_c + \tau_t + \lambda macro_{ct} + \beta X_{ict} + \delta Pol_{ct} + \varepsilon_{ict}$$

Pol_{ct} is the level of expenditure in both retention and reallocation policies in country *c* as a share of GDP scaled by the number on unemployed. This scaling accounts for differences in the unemployment rates across countries and over time and measures the policy intensity per unemployed person. Thus, the policy measures considered here can be loosely be interpreted as percentages of average income spent per unemployed person.[10] $macro_{ct}$ includes the output gap and the log of GDP per capita as additional controls. α_c and τ_t are country and year fixed effects respectively. Including country fixed effects is important to account for country-specific slow-moving variables such as labor market institutions.

[10] The two policies variables include the following categories from the OECD Labor Market Policies database (see Annex 3.1): Retention Policies: (i) benefits administration (12), (ii) workplace training (22), (iii) apprenticeship (24), (iv) employment incentives for maintenance (keeping jobs) (42), (v) partial unemployment benefits (82), and (vi) part-time unemployment benefits (83). Reallocation Policies: (i) placement administration (11), (ii) institutional training (21), (iii) integrated training (23), (iv) employment incentives for recruitment (hiring) (41), (v) direct job creation (60), (vi) start-up incentives (70), (vii) early retirement (90).

Finally, to analyze how the effects of policies vary by demographic and socio-economic characteristics, the policy variables are interacted with the dummies for age, gender, and skill level as defined above:

$$outcome_{ict} = \gamma_{ct} + \beta X_{ict} + \theta Pol_{ct} * X_{ict} + \varepsilon_{ict}$$

The interpretation of the policy effect estimates regressions is subject to some caveats. Reverse causality could arise because policymakers could change their policy stance to target movements in the outcome variable. However, the level of granularity of the outcome, which is at the individual level, relative to the policy indicators, suggests that reverse causation concerns should be minimal. A more relevant concern is the presence of omitted variables. The assumption to identify the effects of policies is that the inclusion of macro controls such as the output gap, or country-year fixed effects in the interacted model, helps to mitigate these concerns, since countries tend to adopt these policies during particular phases of the business cycle.

Figure 3.10 in main text plots overall effects of policy on labor market transition probabilities. Policy impact magnitudes are expressed as a percent of the average value of the labor market transition. For instance, when looking at the impact of reallocation policy on job finding, the job finding probability is on average around 30 percent. A one percentage point change in job reallocation policy boosts job finding probability by 1.3 percent of that 30 percent, which translates into an average 0.4 percentage points change in the job finding probability. The means of the probabilities of job finding, job separation, on-the-job sectoral switch, and on-the-job occupational switch are around 31, 2.7, 3.3, and 12.3 percent in the sample, respectively. Figure 3.10 in main text plots the differential impacts of policy for demographic groups, suggesting that job retention policy support mitigates job separation particularly for the lower-skilled while reallocation support is found to boost the job finding probability particularly for youth and women.

The policy analysis point estimates are generally robust to: (i) excluding one country at a time; (ii) regressing one policy variable at a time; and (iii) inclusion of total unemployment insurance benefits spending as a control.

Annex 3.4 Roy Model of the Labor Market with Search and Matching

The COVID-19 pandemic shock is an unusual shock that can raise questions about applying lessons from previous crises to the current situation. To address some of these concerns and to be able to disentangle the roles of distinct policies, a new search and matching model is developed. The empirical analysis informs the model to explore how the COVID-19 pandemic shock and policies affect labor markets and workers' reallocation. More details about the model setup and calibration are available in Bluedorn, Mondragon, Shibata, and Tavares (forthcoming).

Model

The analysis considers a standard search and matching model to allow for workers' endogenous occupational choices.[1] Workers are risk-neutral and heterogeneous in their productivity in different occupations, while firms have common productivity. Unemployed workers, employed workers, and firms with vacancies are matched, and when a worker and a firm match, they bargain over wages. After the bargain, wages are fixed until the match is dissolved. As in the data, on average, workers who switch occupations on the job experience earnings gains, while workers who switch occupations via unemployment experience earnings losses.

Firms face the risk of a "lockdown" shock associated with a rise in social distancing which impacts occupations asymmetrically by reducing the output produced by a matched firm and a worker. Firms and workers do not have access to financial markets and cannot insure against shocks. This lockdown shock can be transitory or hybrid, where a part of the shock permanently reduces one occupation's productivity. The model is calibrated to the United States, and the shock is calibrated to reproduce the initial increase in unemployment observed in the United States in April 2020.

The government collects labor income taxes that are used to finance an unemployment insurance scheme. The government can also implement retention and reallocation policies. The retention policy is a transfer to firms to support firms' wage bill payments when the match between a firm and a worker stops being profitable due to the lockdown shock. The reallocation policy is a subsidy to firms to reduce vacancy costs and stimulate job creation.

Results

To examine the government policy's impact, this section considers an asymmetric lockdown shock that lasts for four quarters, and four different policy scenarios. The first scenario is the no-policy scenario, where the government does not react to the shock. The second scenario is the reallocation policy scenario, where the government offers a subsidy to firms to reduce vacancy costs and stimulate job creation. The third scenario is the retention policy scenario, where the government offers a transfer to firms to support firms' wage bill payments when the match between a firm and a worker stops being profitable. This transfer has an upper limit

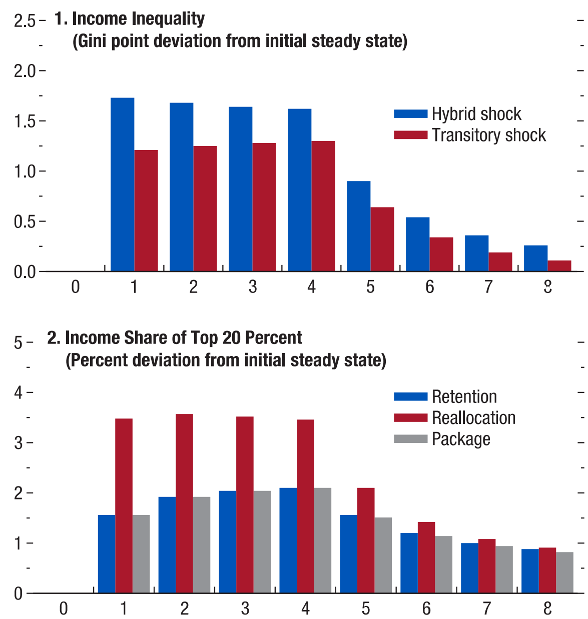
[1] The model is closed related to the work of Huckfeldt (2016), Braxton and Taska (2020), and Dvorkin and Monge-Naranjo (2019).

calibrated to replicate the government expenditure on retention policies observed in the data. The fourth scenario is the package scenario, which considers a package where retention policies are deployed in the first four quarters and reallocation policies are deployed in the subsequent four quarters. All policies in all scenarios are not targeted to a specific sector, and they are financed using government debt. In all the scenarios, unemployment insurance is operating in the background.

This section's main result is that under a hybrid shock, the impact on inequality is larger and permanent without policy support. Under the hybrid shock, workers who were more productive in the more impacted occupation cannot regain their labor productivity. As a result, their wages are permanently lower, leading to an increase in income inequality (Annex Figure 3.4.1, panel 1).

Annex Figure 3.4.1. Impact of Shocks and Policies on Income Inequality

Inequality worsens more when part of the adverse shock is permanent. A package of retention and reallocation policies helps to rein in the relative rise of the richest after a pandemic.



Source: IMF staff calculations.
Note: The *x*-axis indicates the number of quarters after the shock starts. Package comprises a sequence of retention and reallocation policies. Panel 2 shows responses to the hybrid shock.

Regarding the impact of policy on inequalities, retention policies are more potent in reducing inequalities in the short term. In contrast, reallocation policies have a more significant effect in reducing inequalities in the long term (Figure 3.12 in the main text). Retention policies are useful in the short term because they prevent workers from going through unemployment, which can be costly, and have long-lasting impacts, as seen in the empirical analysis

In Annex Figure 3.4.1, panel 2, the bottom quantile income share relative to the pre-shock income share are plotted. Confirming the empirical findings, less-productive/lower-skilled workers are hit harder by the crisis, and retention policies are more effective in the short term. At the same time, the package is more effective in reducing inequalities in the long term. More-productive workers suffer less initially and recover faster. They also tend to benefit more from reallocation than from retention policies in the short term.