Annex 2.1. Data Sources and Country Coverage

All indicators and their respective data sources used in the chapter are listed in Annex Table 2.1.1.

Annex Table 2.1.1. Data Sources

Indicator	Source
Gross Domestic Product, Constant Prices	IMF, World Economic Outlook database
Gross Capital Formation, Constant Prices	IMF, World Economic Outlook database
Final Consumption Expenditure, Constant Prices	IMF, World Economic Outlook database
Total Domestic Demand, Constant Prices	IMF, World Economic Outlook database
Population	IMF, World Economic Outlook database
Total Labor Force	IMF, World Economic Outlook database
Total Employment	IMF, World Economic Outlook database
Share of Population in 15–64	World Bank, World Development Indicators database
Capital Stock	Penn World Tables 9.0
Sectoral Real Value Added (Manufacturing, Services)	World Bank, World Development Indicators database
Banking Crisis	Laeven and Valencia (2013)
General Government Debt	IMF, Global Debt database; World Economic Outlook database
Share of Labor Compensation in GDP	Penn World Tables 9.0
Gini Coefficient	Standardized World Income Inequality Database
Research and Development Expenditure	World Bank, World Development Indicators database
Robot Stock and Shipment	International Federation of Robotics
Domestic Credit to Private Sector	World Bank, World Development Indicators database
Export Value of Goods (bilateral)	IMF, Direction of Trade Statistics database
Financial Openness	Lane and Milesi-Ferretti (2017)
Current Account Balance	IMF, World Economic Outlook database
Current Account Gap	Lee and others (2008)
Regulation of Employment Dismissal	Cambridge University's Centre for Business Research
De Facto Peg Strength	Ghosh and others (2011)
General Government Structural Balance	IMF, World Economic Outlook database
Real Short-term Deposit Rate	IMF, World Economic Outlook database
Banking Regulation Index	Barth, Caprio, and Levine (2013)
Fraction of Bank Application Denied	Barth, Caprio, and Levine (2013)
Bank Concentration	Barth, Caprio, and Levine (2013)
Supervisory Power	Barth, Caprio, and Levine (2013)
Capital Regulation	Barth, Caprio, and Levine (2013)
Bilateral Cross-Border Bank Claims	Bank for International Settlements
Total Headline Support for Financial and Other Sectors	IMF, Fiscal Affairs Department (2009)
Capital Injections	IMF, Fiscal Affairs Department (2009)
Purchase of Assets and Lending by Treasury	IMF, Fiscal Affairs Department (2009)
Central Bank Support with Treasury Backing	IMF, Fiscal Affairs Department (2009)
Central Bank Liquidity Support	IMF, Fiscal Affairs Department (2009)
Guarantees (excl. Deposit Insurance)	IMF, Fiscal Affairs Department (2009)
Upfront Government Financing	IMF, Fiscal Affairs Department (2009)
Crisis-Related Discretionary Fiscal Stimulus	IMF, Fiscal Monitor (2010)
Active Labor Market Policy	OECD, Employment database
Employment Protection Legislation	OECD, Employment database
Inflow/Outflow Rate for Unemployment	OECD, Employment database
Labor Skills	World Input-Output Database
Labor Compensation	World Input-Output Database
Capital Compensation	World Input-Output Database
Sectoral Capital Stock	World Input-Output Database
Sectoral Price Levels	World Input-Output Database
Sectoral Employment Headcount	World Input-Output Database
Sectoral Employment Hours worked	World Input-Output Database

Source: IMF staff compilation.
Note: OECD = Organisation for Economic Co-operation and Development.

The country coverage for the different sections is presented in Annex Table 2.1.2, there are considerable variations in the sample of countries included in the various analytical exercises due to data constraints.

Annex Table 2.1.2. Country Coverage

Albania*; Algeria*; Angola*; Antigua and Barbados*; Argentina*†; Armenia*; _Australia_ †; _Austria_ †; Azerbaijan*; Bahamas, The*; Bahrain*; Bangladesh*•; Barbados*; Belarus*; _Belgium_ †; Belize*; Benin*•; Bhutan*•; Bolivia*; Bosnia and Herzegovina*; Botswana*; _Brazil_ *†; Brunei Darussalam*; _Bulgaria_ *†; Burkina Faso*•; Burundi*•; Cabo Verde*; Cambodia*•; Cameroon*+; _Canada_ †; Central African Republic*•; Chad*+; Chile*†; _China_ *†; Colombia*†; Comoros*•; Congo, Democratic Republic of the*•; Congo, Republic of*+; Costa Rica*†; Croatia*†; Cyprus†; _Czech Republic_ †; Côte d'Ivoire*+; _Denmark_ †; Djibouti*•; Dominica*; Dominican Republic*; Ecuador*; Egypt*; El Salvador*; Equatorial Guinea*; Eritrea*•; _Estonia_ †; Ethiopia*•; Fiji*; _Finland_ †; _France_ †; Gabon*; Gambia, The*•; Georgia*; _Germany_ †; Ghana*+; _Greece_ †; Grenada*; Guatemala*; Guinea*+; Guinea-Bissau*•; Guyana*; Haiti*•; Honduras*+; Hong Kong SAR; _Hungary_ *†; Iceland†; _India_ *†; _Indonesia_ *†; Iran*; Iraq*; _Ireland_ †; Israel†; _Italy_ †; Jamaica*; _Japan_ †; Jordan*; Kazakhstan*; Kenya*•; Kiribati*•; _Korea_ †; Kosovo*; Kuwait*; Kyrgyz Republic*•; Lao P.D.R.*•; _Latvia_ †; Lebanon*; Lesotho*•; Liberia*•; Libya*; _Lithuania_ †; Luxembourg†; Macao SAR; Macedonia, FYR*; Madagascar*•; Malawi*•; Malaysia*; Maldives*; Mali*•; _Malta_ †; Marshall Islands*; Mauritania*+; Mauritius*; _Mexico_ *†; Micronesia*; Moldova*•; Mongolia*; Montenegro, Rep. of*; Morocco*; Mozambique*+; Myanmar*+; Namibia*; Nepal*•; _Netherlands_ †; New Zealand†; Nicaragua*+; Niger*+; Nigeria*+; Norway†; Oman*; Pakistan*; Palau*; Panama*; Papua New Guinea*+; Paraguay*; Peru*†; Philippines*; _Poland_ *†; _Portugal_ †; Puerto Rico; Qatar*; _Romania_ *†; _Russia_ *†; Rwanda*•; Samoa*; San Marino; Saudi Arabia*†; Senegal*•; Serbia*; Seychelles*; Sierra Leone*•; Singapore; _Slovak Republic_ †; _Slovenia_ †; Solomon Islands*•; South Africa*†; Spain†; Sri Lanka*; St. Kitts and Nevis*; St. Lucia*; St. Vincent and the Grenadines*; Sudan*+; Suriname*; Swaziland*; _Sweden_ †; Switzerland†; São Tomé and Príncipe*•; _Taiwan Province_ ; Tajikistan*+; Tanzania*•; Thailand*; Timor-Leste*•; Togo*•; Tonga*; Trinidad and Tobago*; Tunisia*; _Turkey_ *†; Turkmenistan*; Tuvalu*; Uganda*•; Ukraine*; United Arab Emirates*; _United Kingdom_ †; _United States_ †; Uruguay*; Uzbekistan*•; Vanuatu*; Venezuela*; Vietnam*•; Yemen*+; Zambia*+; Zimbabwe*•.

Source: IMF staff compilation.
Notes: Asterisk (*) denotes emerging market and developing economies as classified by the IMF, _World Economic Outlook_ . Crossing (+) denotes commodity-exporting low-income developing countries (LIDC commodity exporters) that meet two conditions: (1) commodities constitute at least 35 percent of the country's total exports, on average, between 1962 and 2014; and (2) net commodity exports accounted for at least 5 percent of its gross trade (exports plus imports), on average, between 1962 and 2014. Circle(•) denotes noncommodity-exporting low-income developing countries (LIDC noncommodity exporters). Obelus(†) denotes OECD and partner countries. Countries in italics denote country sample used for the analysis on robots.

Annex 2.2. Additional Details on Quantifying Post-Crisis Deviations in Activity from Pre-Crisis Trends

This annex provides additional details on the analysis shown in the section "Quantifying post-crisis deviations in activity from precrisis trends."

A. Definition of Banking Crises

Annex Table 2.2.1 lists the banking crises used in the analysis. The definition of a banking crisis is from Laeven and Valencia (2013). It is based on two criteria: significant financial distress (including bank runs and liquidations) and significant government intervention in the banking system (including recapitalization, liability guarantees, and nationalization). The sample includes all banking crises that started between 2007–08.

Annex Table 2.2.1. Banking Crises, 2007–08

Country	Start of Crisis
Systemic Cases	
Austria	2008
Belgium	2008
Denmark	2008
Germany	2008
Greece	2008
Iceland	2008
Ireland	2008
Kazakhstan	2008
Latvia	2008
Luxembourg	2008
Mongolia	2008
Netherlands	2008
Spain	2008
Ukraine	2008
United Kingdom	2007
United States	2007
Borderline Cases	
France	2008
Hungary	2008
Italy	2008
Portugal	2008
Russia	2008
Slovenia	2008
Sweden	2008
Switzerland	2008

Source: Laeven and Valencia (2013).

B. Definitions of Main Data Categories

Deviations from Pre-Crisis Trends

Deviations of GDP and other variables trending from the pre-crisis trend are calculated as follows:

- First, the transitory pre-crisis components are removed by means of low pass filters.[1] While no method of removing transitory components can accommodate the specificities of every country in the sample, the filtering approach by Gourinchas and Obstfeld (2012), where the two-sided Hodrick-Prescott (HP) lowpass filter is used to eliminate transitory components, offers a general method of isolating low frequency (log) GDP movements from the data.[2] The smoothing parameter is set at a higher value (100) than in standard business cycle detrending (6.25 with annual data). With the higher parameter, the estimated trend is less sensitive to short-run business cycle fluctuations and filters out relatively more medium-term influences, such as those of credit cycles.[3] Annex Figure 2.2.1 shows how removing transitory components affects estimation of the pre-crisis trend in the cases of the US. The

[1] An alternative approach is to fit a linear trend to the log-GDP series that has been truncated a few years before the peak of the cycle. This approach produces estimates that are highly sensitive to the length of the truncation period. Furthermore, its cutoff frequency cannot be controlled. Hence it is not used in the chapter.

[2] Estimating the trends with a multivariate filter (as in Berger and others 2015) that accounts for macrofinancial imbalances could in principle provide more accurate estimates of underlying trend. In practice, the HP filter with the smoothing parameter set to 100 works equally well. In addition, the limited availability of data on asset prices precludes a wide application of multivariate filtering.

[3] The "standard" value λ=6.25 has the cutoff frequency of only 8 years.

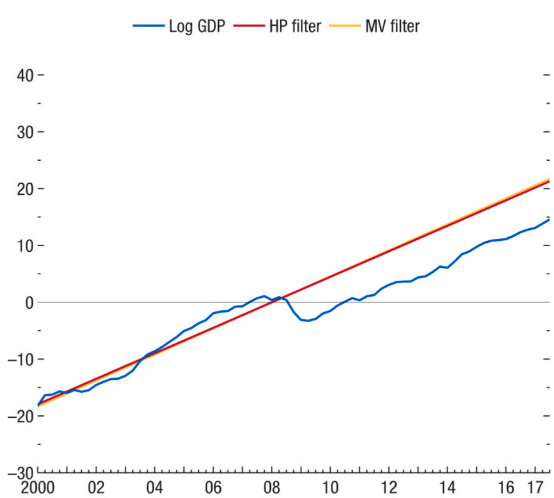
MV filter yields estimates of output deviations that are in agreement with those obtained by applying the HP filter as described above.

- The underlying filtered time series run from 1995 to 2017. While GDP series could have experienced a structural break at the time of the GFC, an analysis shows that the estimated deviations are robust to the presence of a structural break.[4] Annex Figure 2.2.1 shows the relationships between 2011–13 and 2015–17 GDP deviations estimated with and without allowing for a post-GFC structural break. The closeness of both sets of estimated deviations demonstrates the robustness of estimated GDP deviations to the presence of a structural break.

- Second, the trend of the filtered series is calculated over 2000–08. The 2000–08 period is chosen because it is long enough to minimize the influence of shocks in individual years.[5]

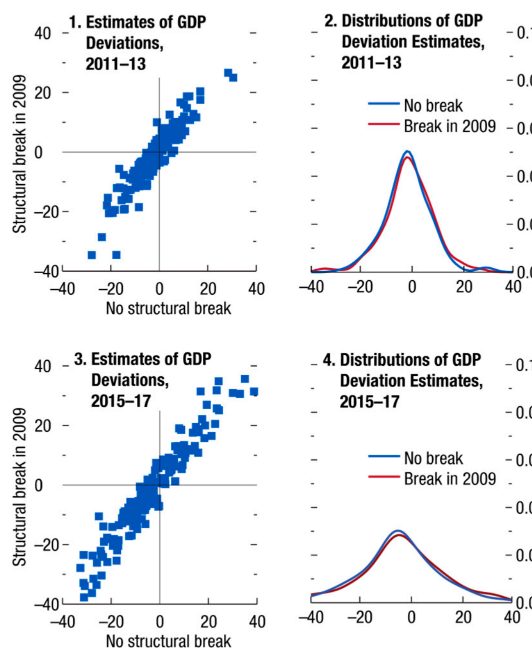
- Finally, the deviations of post-crisis GDP from its pre-crisis trend are calculated as the average differences for 2011–13 and 2015–17.

Annex Figure 2.2.1. Estimates of Precrisis Trends for the United States
(Percent)



Source: IMF staff calculations.
Note: 2008 log GDP normalized to zero. Trend log GDP denotes extrapolated trend of potential GDP during 2000–08. HP = Hodrick-Prescott; MV = multivariate. Potential GDP estimated with the HP filter, lambda = 100. MV filter regressors are headline consumer price index, housing price index, stock prices, credit growth, and capacity utilization.

Annex Figure 2.2.2. Structural Break
(Percent)



Source: IMF Staff Calculations.
Note: Distribution of average percent deviations from precrisis trend.

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[4] The structural break is modelled as 5-σ shock to potential GDP in 2009, calibrated to correspond to the 5-σ shock to headline real GDP.

[5] In the case of the US, Fernald (2015) shows that labor productivity accelerated in the 1990s and that it returned to its long-run trend of approximately 1.5 percent per annum around 2003—well before the 2008 recession. For this reason, calculating post-GFC losses based on periods of faster productivity growth before 2000 could overstate post-GFC output losses. In this chapter's analysis, the trend growth of US labor productivity, calculated as described above, amounts to 1.54 percent per annum. This estimate is in close agreement with the estimate by Fernald.

Deviations of GDP per Worker

Annex Figure 2.2.3 presents the distributions of deviations of 2015–17 deviations of GDP per worker (i.e. labor productivity). Most countries in the banking crisis group experienced negative deviations in labor productivity, with few countries situated to the right of vertical axis. The distribution of deviations in the non-crisis group, while still centered below zero, is considerably more symmetric with a higher mean.

Comparing GDP Deviations with Previous Recessions

Annex Figure 2.2.4 compares the aftermaths of the 2008 and 1982 global recessions. While in the shorter run, both recessions induced similar deviations from the pre-crisis trends, the 2008 impact of the 2008 recession has been felt much longer. In addition, the 2008 recession affected a larger share of global output, as seen by comparing the distributions of weighted and unweighted output deviations.

Employment Deviations

Employment deviations are calculated using the approach by Schanzenbach and others (2017) who track the evolution of the employment ratio and compare it to the "benchmark" value from 2007 as follows:

$$employment\ gap_t = \frac{employment_t}{population_t^{15-65}} \Big/ \frac{employment_{2007}}{population_{2007}^{15-65}} \quad (2.1)$$

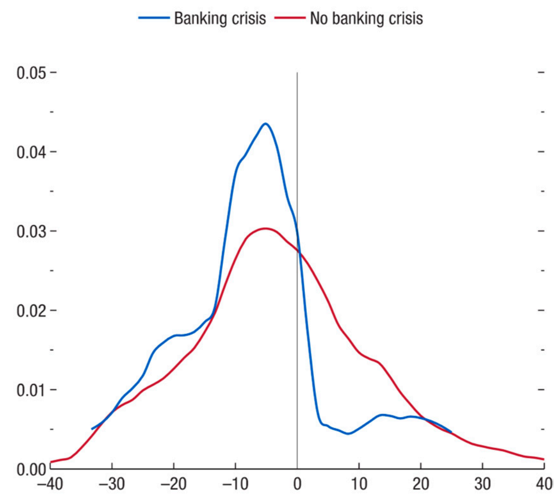
While Schanzenbach and others (2017) estimate employment deviations only for the US, the Chapter extends their analysis to 102 countries.

Deviations of Total Factor Productivity

Post-crisis deviations of total factor productivity (TFP) from its pre-crisis trend are calculated using the standard Cobb-Douglas production function for output per worker and comparing the observed post-crisis values in labor productivity and output per worker with their pre-crisis trends—starred variables in the following equation:

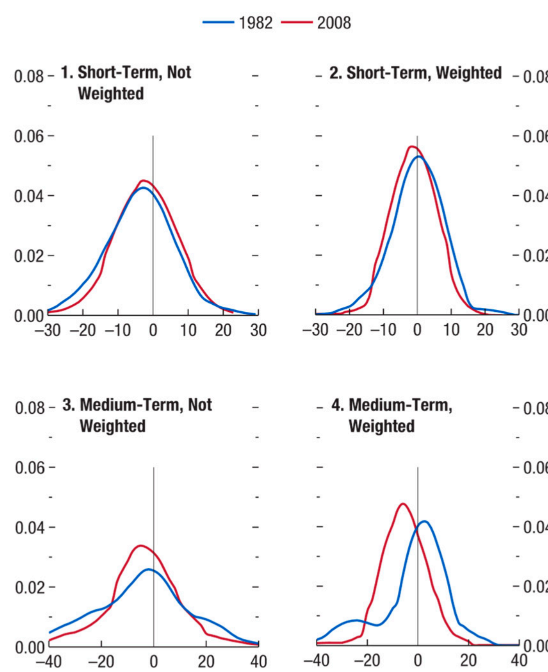
$$\ln\left(\frac{A^*}{A}\right) = \ln\left(\frac{y^*}{y}\right) - \alpha \cdot \ln\left(\frac{k^*}{k}\right) \quad (2.2)$$

Annex Figure 2.2.3. Postcrisis Output per Worker Deviation from Precrisis Trend, 2015–17
(Kernel density)



Sources: Laeven and Valencia (2013); and IMF staff calculations.
Note: Distribution of average percent deviations from precrisis trend, 2015–17. See Annex Table 2.2.1 for banking crises country list.

Annex Figure 2.2.4. Distributions of GDP Deviations after Recessions
(Kernel density)

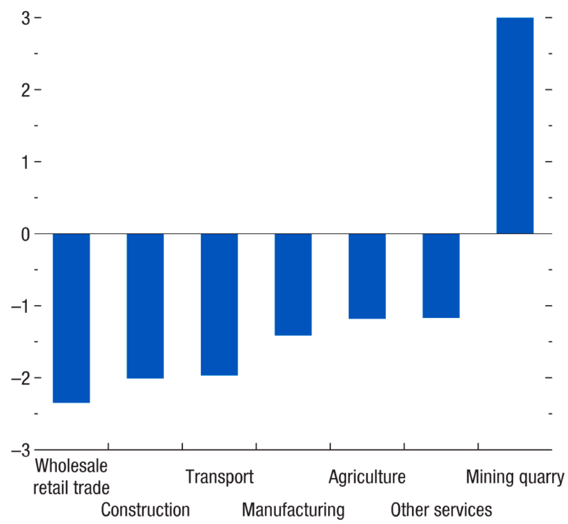


Source: IMF Staff Calculations.
Note: Distribution of GDP percent deviations from precrisis trend. Country weights proportional to purchasing power parity GDP. Short-term = 3–5 years after the recession. Medium-term = 7–9 years after the recession.

Sectoral Capital Stock

As seen in Annex Figure 2.2.5, capital shortfalls are more widespread than just in construction. A broad sample of 38 advanced economies and emerging markets reveals slower average growth rates across many sectors. One exception is the mining and quarrying sector, in part influenced by the continued strength in commodity prices during the early part of the global downturn.

Annex Figure 2.2.5 Change in Postcrisis and Precrisis Growth Rates in Sectoral Capital Stock
(Percent)



Sources: World Input-Output Database; and IMF staff calculations.
Note: The bars depict the difference in average growth rates between 2011–14 and 2000–07.

Construction of Explanatory Variables

Explanatory variables, used in the regression exercises described below, are constructed as follows:

- First, all explanatory variables are averaged over the period 2005-08 to attenuate the effect of idiosyncratic shocks.
- Second, all regressors (except for the banking crisis dummy) are standardized to have zero means and standard deviations of unity.
- Finally, the regressors are winsorized to alleviate influence of outliers.[6]

Tests of Equality of Distributions

Figures 2.3, 2.6 and 2.7 show the distributions of deviations of output, capital stock and total factor productivity respectively. The results of statistical tests of equality of these distributions between countries with and without banking crisis are presented in Annex Table 2.2.2. The table shows the rejection of the null hypothesis of equality of distributions in the cases of output and total factor productivity deviations. However, the distributions of capital stock deviations were not found to be significantly different between the crisis and non-crisis countries.

Annex Table 2.2.2. Tests of Equality of Distributions of 2015–17 Deviations

	Average Percentile	Expected Percentile	P-Value
GDP	39.4	50.3	0.052
Capital Stock	47.7	50.3	0.630
Total Factor Productivity	41.5	50.5	0.079

Source: IMF staff calculations.
Note: Two-sample Wilcoxon rank-sum (Mann-Whitney) test.

Regression Analysis

Probability of a Banking Crisis

The probability of a banking crisis occurring in 2007–08 is given by the following qualitative response model:

$$\Pr\left(banking\ crisis\right) = f\left(regulation, \theta\right), \qquad (2.3)$$

where *regulation* is a measure of various aspects of banking regulation and θ is the set of parameters to be estimated. The index of banking regulation is drawn from Barth, Caprio, and Levine (2013). Results in

[6] The analysis omits countries with large output deviations that were caused by war or political strife.

Annex Table 2.2.3 show that the strength of restriction on banking activities (specifically, stronger restrictions on banks' ability to underwrite, broker, and deal in securities; offer mutual fund products; and engage in insurance underwriting, real estate investment, development, and management) in 2006 is associated with a lower probability of the occurrence of banking crisis in 2007–08 and the coefficient is statistically significant. To test the robustness of the relationship, Annex Table 2.2.4 includes additional influences on the probability of occurrence of banking crisis in 2007–08. The strength of restriction on banking activities remains significant once the additional influences are controlled for.

Annex Table 2.2.3. Probability of Banking Crisis and the Strength of Restrictions on Banking Activities

	Probit	Logit	LPM
Strength of Restrictions on Banking Activities	–0.72 ***	–1.27 ***	–0.18 ***
Constant	–1.04 ***	–1.79 ***	0.19 ***
Observations	116	116	116
R^2			0.17

Source: Barth, Caprio and Levine (2013); IMF staff calculations.
Note: LPM = linear probability model.
*** p < 0.01, ** p < 0.05, * p < 0.1.

GDP Deviations: Banking Crisis, Vulnerabilities, Policies and Economic Structure

Annex Table 2.2.5 presents an analysis of factors that determine the deviation of GDP during 2011–13. The analysis considers three sources of variation: vulnerabilities (the first two columns), economic structure and policies. Results show that the occurrence of banking crisis has a significant negative effect on GDP, underscoring the importance of sound banking regulation. Countries whose pre-recession credit growth was relatively more rapid suffered comparatively more damages. The analysis using the pre-crisis CA gap (based on Lee and others 2008) as an explanatory variable shows that excess external imbalances constituted an important vulnerability that was associated with larger post-crisis GDP losses.

Annex Table 2.2.6 presents an analysis of factors driving the deviations in investment during 2011–13. The important finding is that demand exposure to advanced economies weighs on investment even in countries without banking crises, illustrating the importance of the trade channel for investment.

Annex Table 2.2.4. Banking Crisis and Regulations: Probit Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Strength of Restrictions on Banking Activities	−0.72 ***					−0.71 ***	−0.61 ***	−0.60 ***				−0.60 **	−0.65 **	−0.43	−0.46 *
Fraction of Bank Application Denied		−1.50 ***							−1.55 ***	−1.60 *	−1.07 ***	−1.13 ***	−1.32 **	−0.90 **	−1.25 *
Bank Concentration			0.05												
Supervisory Power				−0.10											
Capital Regulation					−0.16										
Share of Interest Borrowing from G5						−0.01			0.27				0.35		
Financial Openness							1.21 **			2.48 **					1.94 *
Demand Exposure to Advanced Economies								3.13 **			4.89 **			3.36	
Constant	−1.04 ***	−1.14 ***	−0.74 ***	−0.83 ***	−0.88 ***	−1.01 ***	−0.98 ***	−0.90 ***	−1.15 ***	−1.17 **	−0.81 ***	−1.11 ***	−1.20 ***	−0.87 ***	−1.10 ***
Observations	116	54	52	98	98	111	116	115	53	54	54	51	50	51	51

Source: Barth, Caprio, Levine (2013); and IMF staff calculations.

Note: Group of Five (France, Germany, Netherlands, United Kingdom, and United States). G5 = Group of Five.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Annex Table 2.2.5. Impact on 2011–13 GDP Deviations from One Standard Deviation Increase in Drivers

	(1)	(2)	(3)	(4)
Banking Crisis in 2007–08	−4.32 **	−2.01	−6.53 ***	−4.21 **
Domestic Credit Growth	−2.70 **	−5.37 ***		
Demand Exposure to Advanced Economies	−13.35 ***	−6.19		
Demand Exposure to China	1.07	3.04		
Financial Openness	−3.35 *	−3.04		
CA Balance	0.65			
Precrisis GDP Growth	−0.55	3.31 ***	−0.57	−0.94
CA Gap		2.10 ***		
Share of Manufacturing in GDP			0.15	
Difficulty of Dismissal			−1.56 **	
Precrisis GG Debt Change				−8.33 ***
De Facto Peg Dummy				−1.79 **
Constant	−3.49 ***	−4.04 ***	−2.00 **	−0.95
Observations	163	64	107	83
R^2	0.18	0.58	0.16	0.29

Source: IMF staff calculations.

Note: Banking crisis in 2007–08 is dummy variable, based on Laeven and Valencia (2013). See Annex Table 2.2.1 for banking crises country list. CA = current account; CA Gap = the excess external balance, Lee and others (2008); GG = general government.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Annex Table 2.2.6. Impact on 2011–13 Investment Deviations from One Standard Deviation Increase in Drivers

	All Countries		Countries without Banking Crisis in 2007–08	
Banking Crisis in 2007–08	−11.59 ***	−3.52		
Domestic Credit Growth	-6.81 **	−12.05 ***	−6.04 *	−8.31
Demand Exposure to Advanced Economies	−24.81 *	−14.94	−25.17 *	−19.91
Demand Exposure to China	3.87	20.80 ***	4.19	22.70 ***
Financial Openness	−0.50	2.47	−2.81	−1.73
CA Balance	5.46 **		4.43 *	
Precrisis GDP Growth	−5.17 *	6.88 **	−5.36 *	7.48 **
CA Gap		10.62 ***		12.79 ***
Constant	−9.16 ***	−9.22 ***	−9.37 ***	−9.59 ***
Observations	135	62	114	42
R^2	0.23	0.70	0.16	0.64

Source: IMF staff calculations.

Note: Banking crisis in 2007–08 is dummy variable, based on Laeven and Valencia (2013). See Annex Table 2.2.1 for banking crises country list. CA = current account; CA Gap = the excess external balance, Lee and others (2008); GG = general government.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

GDP Deviations: AEs versus EMDEs, Vulnerabilities, Policies and Economic Structure

The differences in the post-recession GDP deviations between advanced and emerging markets (EMs) are presented in Annex Table 2.2.7. As above, rapid credit growth is a robust predictor of more negative short-run GDP deviations for both AEs and EMs. The two groups of countries differ in their responses to the pre-crisis current account (CA) balance, labor market flexibility, demand exposure to AEs and exposure to global financial markets.[1]

An analysis of the effectiveness of post-recession policies is presented in Annex Table 2.2.8. GDP deviations during 2015–17 are regressed on different policy variables as well as on the GDP deviation during 2011–13. The latter variable controls for the strength of the initial crisis shock. The analysis shows that total post-recession fiscal support was effective in reducing the post-recession decline in GDP. In addition, capital injections and guarantees are also found to be significant and effective policy measures.

Constructing Measures of Labor Market Churn

The chapter follows the methodology of Elsby, Hobijn, and Sahin (2012) to estimate the parameters that characterize labor market dynamism as follows. The law of motion for the rate of unemployment u_t is represented by

$$\frac{du_t}{dt} = s_t(1-u_t) - f_t u_t, \qquad (2.4)$$

where s_t is the monthly rate of inflow into unemployment and f_t is the monthly rate of outflow from unemployment. For reasons of data availability, the "continuous" time equation (2.4) is mapped into one at annual frequencies as shown in equations (2.5–2.6). The flow-steady rate of unemployment u^*_t is given by

$$u_t^* = \frac{s_t}{s_t + f_t}. \qquad (2.5)$$

If flow hazards are constant within a year, the law of motion for the rate of unemployment becomes

$$u_t = \lambda_t u_t^* + (1-\lambda_t) u_{t-12}, \qquad (2.6)$$

where λ_t is the annual rate of convergence to the steady state

$$\lambda_t = 1 - e^{(-12(s_t + f_t))}. \qquad (2.7)$$

Using the expression for probability that an unemployed worker exits unemployment within d months the expressions (2.6–2.7) are inverted to back out the annual estimates of f_t and s_t.

[1] Explanatory variables in Annex Tables 2.2.7–2.2.8 are averaged over 2005–08.

Annex Table 2.2.7. Impact on 2011–13 GDP Deviations from One Standard Deviation Increase in Drivers by Country Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AEs	EMs	AEs	EMs	AEs	EMs	AEs	EMs
Domestic Credit Growth	–4.96 **	–4.79 ***	–5.43 ***	–5.71 **				
Demand Exposure to Advanced Economies	9.01	–7.20	4.40	–8.27				
Demand Exposure to China	3.88	7.33 **	6.56 *	4.98				
Financial Openness	–3.34	–3.68	–2.30	–21.43				
CA Balance	4.03 ***	–0.42						
Precrisis GDP Growth	–1.64	–0.27	2.77 *	3.11	–3.17	–1.55	–2.22	–0.45
CA Gap			2.49 ***	1.23				
Share of Manufacturing in GDP					3.18	0.34		
Difficulty of Dismissal					–1.72 *	–2.27 **		
Precrisis GG Debt Change							–11.85 ***	–10.27 ***
De Facto Peg Dummy							–2.50 ***	–1.27
Constant	–6.99 ***	–4.46 ***	–6.28 ***	–6.91	–8.84 ***	–1.07	–2.58	–0.42
Observations	33	83	32	32	34	52	34	48
R^2	0.63	0.21	0.69	0.44	0.17	0.10	0.31	0.15

Source: IMF staff calculations.

Note: AEs = advanced economies; CA = current account; CA Gap = the excess external balance, Lee and others (2008); EMs = emerging markets; GG = general government.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Annex Table 2.2.8. Impact on 2015–17 GDP Deviations from One Standard Deviation Increase in Drivers

Total Headline Support for Financial and Other Sectors	0.20 **							
Capital Injections		1.90 *						
Purchase of Assets and Lending by Treasury			0.21					
Central Bank Support with Treasury Backing				–14.35				
Central Bank Liquidity Support					–0.25			
Guarantees (excluding Deposit Insurance)						0.24 *		
Upfront Government Financing							0.31	
Crisis-Related Discretionary Fiscal Stimulus								–0.78
Banking Crisis in 2007–08	–0.17	–1.74	2.88	3.54 *	3.06	–1.35	1.71	2.25
GDP Deviation 2011–13	1.12 ***	1.05 ***	1.10 ***	1.08 ***	1.10 ***	1.06 ***	1.09 ***	1.33 ***
Constant	–5.95 ***	–5.08 ***	–4.79 **	–4.04 **	–2.04	–5.12 **	–4.72 **	–1.33
Observations	29	29	29	29	29	28	29	19
R^2	0.62	0.60	0.53	0.54	0.54	0.60	0.53	0.50

Source: IMF staff calculations.

Note: Banking crisis in 2007–08 is dummy variable, based on Laeven and Valencia (2013). See Annex Table 2.2.1 for banking crises country list.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Annex 2.3. Robot Diffusion and its Employment Impact in the Aftermath of the Crisis

This annex provides additional details on the analyses shown in Figure 2.10 in the main text on technology adoption and for Box 2.2 on the impact of robot diffusion on employment. Annex Table 2.3.1 presents the sectors included in the analysis on robots.

Annex Table 2.3.1. Sectors, Individual Industries, and Abbreviations Used in Chapter, ISIC Revision 4 and IFR Sector Classifications

Sector Name	WIOD Sectors Included (ISIC Revision 4)	IFR Sectors Included
Agriculture	Agriculture, hunting, forestry and fishing	Agriculture, forestry, fishing
Automotive	Transport equipment	Automotive
Mining	Mining and quarrying	Mining and quarrying
Food and Beverages	Food, beverages, and tobacco	Food and beverages
Metal	Basic metals and fabricated metal; Machinery, not elsewhere classified	Metal
Electronics	Electrical and optical equipment	Electrical/electronics
Glass and Ceramics	Other non-metallic mineral	Glass, ceramics, stone, mineral products
Paper and Printing	Pulp, paper, paper, printing and publishing	Paper
Utilities	Electricity, gas, and water supply	Electricity, gas, water supply
Construction	Construction	Construction
Education, Research, and Development	Education, scientific research and development	Education/research/development
Plastic and Chemicals	Chemicals and chemical products; rubber and plastics	Plastic and chemical products
Textiles and Leather	Textiles, wearing apparel and leather products	Textiles
Wood and Furniture	Wood and products of wood and cork	Wood and furniture

Source: IMF staff compilation.
Note: IFR = International Federation of Robotics; ISIC = United Nations International Standard Industrial Classification of All Economic Activities; WIOD = World Input-Output Database.

A. Additional Details on Data

The main data on robots come from the International Federation of Robotics (IFR), which compiles information on worldwide shipment and stock of industrial robots from national federations of robot manufacturers, consisting of nearly all industrial robot suppliers worldwide (IFR, 2017). An industrial robot as defined by the International Organization for Standardization (ISO) is an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation application." This definition limits the set of industrial robots and excludes dedicated industrial robots that serve one purpose.[1] Industrial robot data are broken up by destination country, year, industry and technological application. In the 2017 data publication, IFR provides industrial robot shipment and stock data on 75 countries, although the industry level coverage starts at a much later year than the country aggregate data coverage.[2] The industry level

[1] Before 2001, Japan's data included both multipurpose industrial robots and dedicated industrial robots (e.g. equipment dedicated for loading/unloading machine tools, assembly on printed circuit boards, storage and retrieval systems, etc.), while other countries, in principle, have only reported data on multipurpose industrial robots. As of 2001, dedicated robots are excluded from the flow statistics. The operational stock data, however, continues to include a fairly large share of dedicated robots. Statistics on new installations and flows from 2001 onward are internationally comparable with Europe and North America.

[2] The earliest available data at the industry level starts in 1993 but limited to nine countries, the coverage extends to 38 countries in 2005.

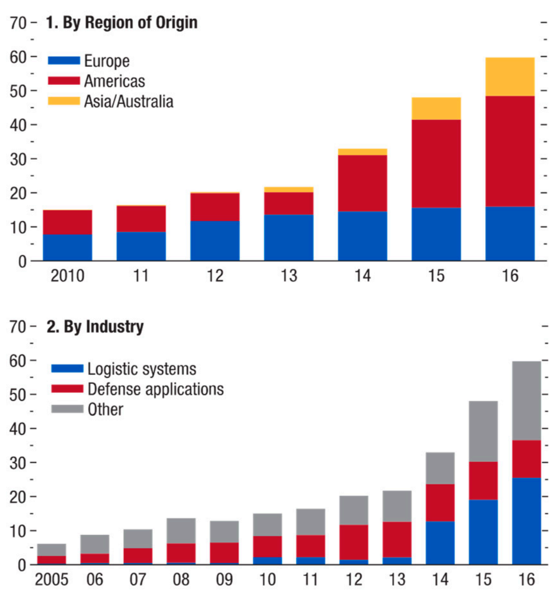
data is broken down by industrial branches in accordance with the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 for 2010 and revisions 2 or 3 in earlier years.

Service robots are defined as robots that perform useful tasks for humans or equipment excluding industrial automation application. Services robots can be divided further into personal service robots that are used for non-commercial tasks, usually by lay persons— for instance, domestic service robot, automated wheelchair, and personal mobility assist robot —or professional service robots, used for commercial tasks, usually operated by a properly trained operator, examples of the latter are cleaning robot for public places, delivery robot in offices or hospitals, firefighting robot among others.

The data coverage on service robots is sparse and is limited to only the supplier region. Service robot data is compiled based on market surveys that IFR sends to companies worldwide. As of 2016, the list of service robot suppliers has been expanded to more than 700 companies. Despite improvement in the response rate over the years, IFR urges that "the data reported still underestimate the true sales figures and installed base of service robots. They should therefore be considered a minimum level of the installed base of service robots" (IFR, 2017).[3] Moreover, service robot data are only available at the regional level where they are produced (Europe, Americas, and Asia/Australia) and by application. Because of this data limitation in service robots, it is not possible to infer relationship between service robot diffusion and other economic variables in the country and industry where the service robot is deployed. Hence, only descriptive statistics about service robots are provided, whereas the regression analysis is conducted solely based on industrial robots.

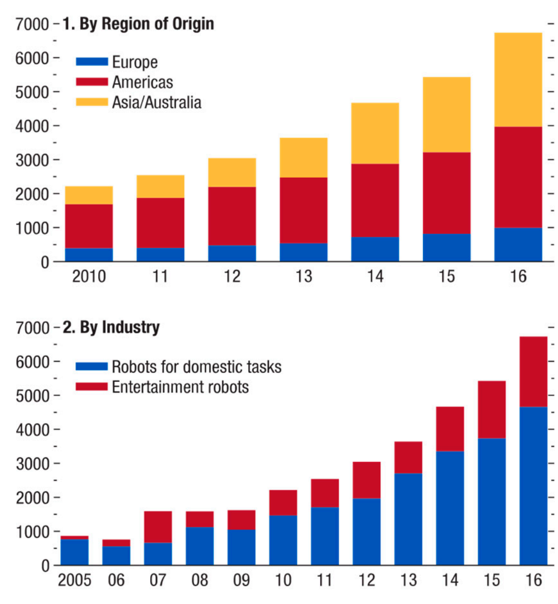
Annex Figures 2.3.1 and 2.3.2 provide the breakdown of professional and personal service robots, respectively. Over half of the surveyed service robot manufacturers are in the Americas for both professional and personal use. The most prevalent applications of professional service robots are in logistics and defense, whereas personal service robots are mainly employed to carry out tasks in domestic households. The number of service robots has increased five-fold for professional services robots since

Annex Figure 2.3.1. Sales of Robots for Professional Services
(Thousands of units)



Sources: International Federation of Robotics; and IMF staff calculations.
Note: Data on service robots is only available by origin regions for Asia/Australia, Americas, and Europe.

Annex Figure 2.3.2. Sales of Robots for Domestic/Personal Services
(Thousands of units)



Sources: International Federation of Robotics; and IMF staff calculations.
Note: Data on service robots is only available by origin region for Asia/Australia, Americas, and Europe.

[3] The amount of sales information available also differs significantly between various application areas.

2010, starting from a relatively small base, whereas for personal services robots, the number of units have increased three-fold since 2010, starting from a much bigger base compared to professional service robots.

To assess the employment effects of automation by industrial robots at the sectoral level, the industrial robot data is merged with data from the World Input-Output Database (WIOD) by country and sector. The 2016 WIOD (Timmer and others, 2015) provides information on labor (hours worked, number of employees, and labor compensation) between 2000 and 2014 for 43 countries (representing more than 85 percent of world GDP) and 56 industries at the 2-digit ISIC revision 4 level. Data on labor skills (three different skills based on highest level of education obtained) come from the 2013 version of the WIOD's Socio Economic Account that provides data on number of hours worked by low, medium and high skilled workers as well as their respective share of overall labor compensation for the period 1995–2009.[4] The combined IFR and WIOD data covers 38 countries (Annex Table 2.1.2, countries in italics) and 14 industries (Annex Table 2.3.1).

Robot Density

To provide a meaningful comparison of industrial robot usage across countries and industries, it is important to account for the differences in sizes of industries in various countries. Robot density in industry *i* and country *j* in year *t* is defined as the number of multipurpose industrial robot shipment per thousand hours worked by persons employed in industry *i*,[5] i.e.,

$$Robot\ Density_{ijt} = \frac{Robot\ Shipment_{ijt}}{thousand\ hours\ worked_{ijt}}. \tag{2.8}$$

In contrast to IFR and Graetz and Michaels (forthcoming) who define robot density as the stock of robots per worker and stock of robots per million hours worked, respectively, the definition of robot density in this chapter uses robot shipment in the numerator rather than robot stock. Thus, it is a flow variable rather than a stock variable and can be interpreted as the rate of change in robot usage per thousand hours worked in a given year. The definition in this chapter is closer in spirit to that of Acemoglu and Restrepo (2017) who define exposure to industrial robots as the difference in stock of industrial robots for industry *i* for two given time periods divided by number of workers in the same industry. The main reason to employ industrial robot shipment rather than stock data is because the former is more accurate, especially in later years (IFR, 2017 Introduction, p28).[6]

B. Assessing the Role of Crisis Exposure

Crisis Exposure and Robot Penetration

The underlying test of medians in Figure 2.10 is based on a simple quantile regression of robot density on a high loss dummy for the sample of AEs. The results are displayed in Annex Table 2.3.2 and show that the industries in AE countries with higher output deviations in post-crisis periods tend to experience lower robot diffusion compared to those in AE countries with lower post-crisis output deviations.

Annex Table 2.3.2. Crisis Exposure and Robot Density, Test in Median

	Robot Density
High Output Loss	–0.016 *
	(0.008)
Constant	0.017 **
	(0.007)
Observations	27

Source: IMF staff calculations.
Notes: Median regression of robot density on high output deviation dummy. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[4] Timmer and others (2015) provide more details about the construction of the database and discuss additional features.

[5] The use of hours instead of number of workers is preferred as workers can differ in the number of hours that they work.

[6] While Graetz and Michaels (forthcoming) construct their robot stock data using the perpetual inventory method, the choice of appropriate depreciation rate is not clear.

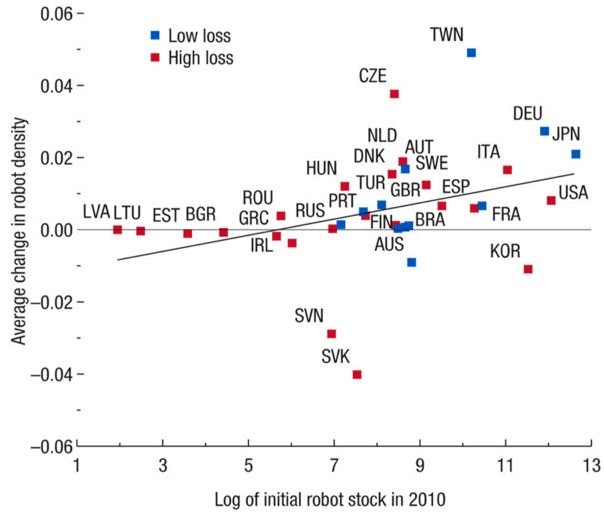
Moreover, this result is not an artefact of convergence as shown in Annex Figure 2.3.3, regardless of initial levels of robot stock, countries are increasing robot diffusion.

A more rigorous method to estimate the impact of crisis exposure on robot diffusion is to employ a difference-in-differences (diff-in-diff) specification at the industry-country level. The first difference exploits variation at the industry-country (*i,j*) level in the difference in average changes in robot density for the post-crisis period (2010–14) relative to pre-crisis (2005–08), and the second difference assesses whether automation via robots advanced at a different pace for industries located in countries with high post-crisis activity deviations relative to pre-crisis. The specification is as follows:

$$Avg\Delta Robot\ Density_{ij}^{Post-PreCrisis} = \alpha + \beta * High\ Loss_j + \delta_i + \varepsilon_{ij}, \qquad (2.9)$$

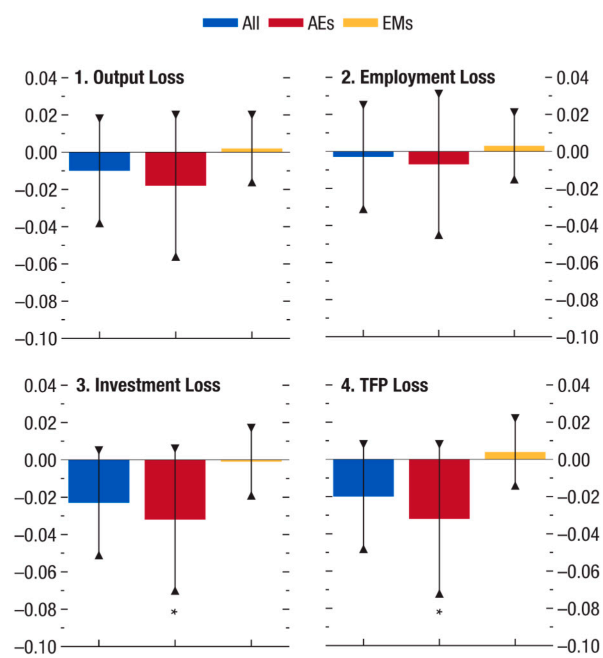
where $Avg\Delta Robot\ Density_{ij}^{Post-PreCrisis}$ is the difference in averages of year-on-year change in robot density in industry *i* and country *j* as defined in (1) for the pre-crisis (2005–08) and post-crisis (2010–14) periods;[7] the dummy variable $High\ Loss_j$ equals one if country *j* experienced above-median losses in activity (as calculated in Annex 2.2 for output, investment and employment) relative to pre-crisis trends and zero otherwise, and δ_i controls for time-invariant industry fixed effects. To account for differences of crisis exposure and penetration in advanced economies (AEs) versus emerging market economies (EMs), the estimation is conducted on the full sample and subsequently separately on subsamples consisting of AEs and EMs, respectively. Annex Figure 2.3.4 and Annex Table 2.3.3 report the estimation results and provide industry-country level evidence in addition to the country-level evidence in the main text (Figure 2.10). It shows that among industries in AEs that experienced relatively higher investment and TFP losses, there is a relatively higher decrease (lower increase) in average change in robot density post- versus pre-crisis compared to industries in AEs that suffered lower investment and TFP losses.

Annex Figure 2.3.3. Average Change in Robot Density (2010–14) and Initial Robot Stock in 2010



Sources: International Federation of Robotics; and IMF staff calculations.
Note: Data labels in the figure use International Organization for Standardization (ISO) country codes.

Annex Figure 2.3.4. Effect of Crisis Exposure on Robot Diffusion
(Average change in robot density, postcrisis minus precrisis)



Sources: International Federation of Robotics; World Input-Output Database; and IMF staff calculations.
Note: Robot density is defined as robot shipment/1,000 hours worked. Error bars around coefficient estimate are two standard errors. Losses are based on calculations Annex 2.2.B. AEs = advanced economies; EMs = emerging markets; TFP = total factor productivity.
* p < .10; ** p < .05; *** p < .01.

[7] The change in industrial robot density can be thought of as the change in the rate of change of industrial robots per million hours worked.

Annex Table 2.3.3. Cross-Section Difference-in-Differences Estimation of Impact of Crisis on Robot Density

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Output Loss			Employment Loss			Investment Loss			TFP Loss		
	All	AEs	EMs	All	AEs	EMs	All	AEs	EMs	All	AEs	EMs
High Loss	−0.010	−0.018	0.002	−0.003	−0.007	0.003	−0.023	−0.032 *	−0.001	−0.020	−0.032 *	0.004
	(0.014)	(0.019)	(0.009)	(0.014)	(0.019)	(0.009)	(0.014)	(0.019)	(0.009)	(0.014)	(0.020)	(0.009)
Constant	0.006	0.011	−0.001	0.002	0.004	−0.001	0.012	0.017	0.000	0.011	0.019	−0.002
	(0.008)	(0.012)	(0.004)	(0.008)	(0.011)	(0.004)	(0.008)	(0.011)	(0.005)	(0.008)	(0.012)	(0.004)
Observations	517	377	140	517	377	140	517	377	140	517	377	140
R^2	0.141	0.18	0.126	0.14	0.178	0.126	0.145	0.184	0.126	0.144	0.184	0.127
Country Fixed Effect	No	No	No	No	No	No	No	No	No	No	No	No
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Sources: International Federation of Robotics; World Input-Output Database; and IMF staff calculations.

Notes: Dependent variable = difference (post minus precrisis) in average change in robot density (2005–08, 2010–14). High Loss equals 1 if a country experienced above-median losses in activity (as calculated in Annex 2.2.B). Classification of advanced economies and emerging markets follow groupings indicated in Annex Table 2.1.2. Robust standard errors are in parentheses. AEs = advanced economies; EMs = emerging markets; TFP = total factor productivity.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C. Sectoral Analysis

Effect of Robot Penetration on Employment

The analysis on the impact of change in robot density on employment follows the main methodology used in Graetz and Michaels (*forthcoming*) and Acemoglu and Restrepo (2017) and employs an ordinary least squares estimation that relate the average employment growth for the post-crisis period (2010–14) to the average change in robot density over the same period while controlling for country-industry specific characteristics and industry and country fixed effects. The specification is as follows:

$$Avg\ \%\Delta EMPL_{ij} = \alpha + \beta * Avg\Delta Robot\ Density_{ij} + \boldsymbol{\gamma} * \boldsymbol{controls}_{ij} + \delta_i + \mu_j + \varepsilon_{ij}, \qquad (2.10)$$

where $Avg\ \%\Delta EMPL_{ij}$ is the average percentage change in employment growth in industry *i* and country *j;* $Avg\Delta Robot\ Density_{ij}$ is average year-on-year change in robot density; the country-industry specific controls include the 2010 levels of industry average wage and the capital-labor ratio; δ_i controls for industry fixed effects, and μ_j controls for country fixed effects. The regression is further weighted using industries' 2010 share of workers within each country. The results reported in Box 2 (Figure 2.2.1) are those for high output loss sample as well as for the sample of AEs with high post-crisis losses in Annex Table 2.3.4 columns (2) and (4), respectively. The results based on investment and TFP deviations are similar to those using output deviations, but estimation results obtained from the employment deviations exercise are not significant and much smaller in magnitude.

Annex Table 2.3.4. Ordinary Least Squares Estimation of Impact of Robot Adoption on Employment Using Output Loss

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Advanced Economies		Emerging Markets	
	Full Sample	High Output Loss	Low Output Loss	High Output Loss	Low Output Loss	High Output Loss	Low Output Loss
Average Δ Robot Density$_{2010–14}$	−0.010	−0.021 ***	0.006	−0.021 ***	0.008	−0.117	0.457 **
	(0.007)	(0.005)	(0.009)	(0.005)	(0.010)	(0.210)	(0.186)
Capital to Labor Ratio$_{2010}$ (log)	0.010 ***	0.007	0.008 **	0.002	0.003	−0.004	0.013
	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.016)	(0.009)
Wage$_{2010}$ (log)	0.013 *	0.047 ***	0.003	0.040 **	−0.011	0.050 *	0.012
	(0.007)	(0.014)	(0.005)	(0.017)	(0.010)	(0.028)	(0.008)
Constant	−0.049 **	−0.145 ***	−0.029	−0.138 **	0.031	−0.125 ***	0.068 ***
	(0.025)	(0.050)	(0.019)	(0.058)	(0.037)	(0.045)	(0.007)
Observations	457	258	199	204	130	54	69
R^2	0.599	0.509	0.78	0.547	0.414	0.592	0.782
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Sources: International Federation of Robotics; World Input-Output Database; and IMF staff calculations.

Notes: Dependent variable = percentage change in employment growth averaged over 2010–14. High loss equals 1 if a country experienced above-median losses in activity (as calculated in Annex 2.2.B). Postcrisis equals 1 in years 2010–14. Classification of advanced economies and emerging markets follow groupings indicated in Annex Table 2.1.2. Robust standard errors are in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Hollowing Out of The Employment-Skills Distribution

To determine the hollowing out effects documented by Autor, Levy, and Murnane (2003) and Goos, Manning, and Salomons (2014) across a larger sample of economies in the post-crisis period, the regression analysis in equation (4) is conducted exclusively on high loss countries (above median-loss) and further divided into subsamples based on an industry's share of medium skilled workers (above- or below-median). The measure of medium skills is based on level of educational attainment of the worker compiled by WIOD. Three types of labor skills are distinguished. To classify as medium skilled labor, WIOD uses the 1997 International Standard Classification of Education (ISCED) classification of the worker having attained (Upper) secondary and / or post-secondary non-tertiary education (WIOD 2013). The main analysis uses the latest available data for the medium skill labor share in 2009. The result reported in Box 2 Figure 2.2.2 is based on the regression results reported in Annex Table 2.3.5, in column (1) and (3). In industries in high output loss countries that have relatively higher share of medium skilled workers, the relationship between robot penetration and employment is negative, this result is driven mainly by the AEs. This negative relationship also holds for industries in countries with above-median employment and investment losses.

Annex Table 2.3.5. Ordinary Least Squares Estimation of Impact of Robot Adoption on Employment by Medium Skills and High Output Loss

	(1)	(2)	(3)	(4)	(5)	(6)
			Advanced Economies		Emerging Markets	
	High medium skill	Low medium skill	High medium skill	Low medium skill	High medium skill	Low medium skill
Average Δ Robot Density$_{2010–14}$	–0.019 **	–0.026	–0.016 **	–0.011	0.149	–0.762
	(0.008)	(0.030)	(0.007)	(0.030)	(0.199)	(0.684)
Capital to Labor Ratio$_{2010}$ (log)	0.007	0.010	–0.004	0.006	0.014	–0.004
	(0.005)	(0.006)	(0.006)	(0.007)	(0.018)	(0.021)
Wage$_{2010}$ (log)	0.039 ***	0.005	0.010	0.005	0.039	0.128
	(0.012)	(0.018)	(0.024)	(0.018)	(0.022)	(0.135)
Constant	–0.123 ***	–0.011	–0.038	–0.012	–0.066	–0.079
	(0.037)	(0.057)	(0.073)	(0.055)	(0.066)	(0.097)
Observations	131	127	104	100	27	27
R^2	0.588	0.767	0.467	0.851	0.906	0.634
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Sources: International Federation of Robotics; World Input-Output Database; and IMF staff calculations.

Notes: Dependent variable = percentage change in employment growth averaged over 2010–14. High output loss indicates that a country experienced above-median losses in output (as calculated in Annex 2.2.B). High (low) medium skills indicate that the industry's share of medium-skilled workers is above (below) median. Average change in robot density is the year-on-year change in robot density averaged over 2010–14. Control variables are 2010 value of capital services to wage bill (in logs) and wages per worker (in logs) in 2010. Regressions are weighted by 2010 within-country employment shares. Classification of advanced economies and emerging markets follow groupings indicated in Annex Table 2.1.2. Robust standard errors are in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Labor Market Policies

To explore whether the impacts of robot penetration on employment differ across countries based on the extent of labor market policies that affect labor market flexibility and resilience, regression analysis is conducted on samples divided by high versus low losses and by different labor market policy measures. There are four specific measures of labor market policy under consideration:

a) above- (high) and below-median (low) active labor market policy (ALMP) spending as share of GDP (2000–05 average)

b) ease of dismissal index (CBR dismissal) as measured by the University of Cambridge's Leximetric datasets (2000–05 average),[8] with above-median (high) dismissal index indicating more stringent regulations for worker dismissal

c) labor churn rate as calculated in Annex 2.2 (2005–08 average) that proxies the degree of initial flexibility in labor markets (measured by pre-crisis exit from and entry into unemployment) with above-median (high) rates indicating a more flexible labor market

d) employment protection legislation (EPL) index compiled by the OECD (for 2008), with above-median (high) index pointing to more protective labor market policies towards workers

The results are displayed in Annex Table 2.3.6 and correspond to Box 2.2 Figure 2.2.3 based on output deviations.

Reference

See Chapter for the list of references.

[8] This index is based on nine detailed sub-categories that encompass various dimensions of dismissal law covering 117 countries for 1970–2013: https://www.repository.cam.ac.uk/handle/1810/256566.

Annex Table 2.3.6. Ordinary Least Squares Estimation of Impact of Robot Adoption on Employment by Labor Market Policies and Output Loss

	High Output Loss								Low Output Loss							
	More Flexible Labor Market				Less Flexible Labor Market				More Flexible Labor Market				Less Flexible Labor Market			
	ALMP	Job Churn	Dismissal	EPL	ALMP	Job Churn	Dismissal	EPL	ALMP	Job Churn	Dismissal	EPL	ALMP	Job Churn	Dismissal	EPL
Average Δ Robot Density$_{2010–14}$	–0.021	–0.032	–0.005	–0.012	–0.018 ***	–0.040 **	–0.018 ***	–0.024 ***	0.002	–0.010	0.004	0.011	0.016	0.005	0.008	–0.013
	(0.029)	(0.037)	(0.053)	(0.032)	(0.006)	(0.019)	(0.006)	(0.005)	(0.014)	(0.035)	(0.015)	(0.012)	(0.018)	(0.018)	(0.014)	(0.013)
Capital to Labor Ratio$_{2010}$ (log)	–0.003	0.006	–0.009	0.020 ***	0.004	0.013	0.012 **	0.007	–0.002	–0.010 ***	0.009 **	0.007	0.013 *	0.004	0.007	0.011
	(0.010)	(0.018)	(0.010)	(0.004)	(0.006)	(0.008)	(0.006)	(0.008)	(0.004)	(0.003)	(0.004)	(0.004)	(0.007)	(0.006)	(0.006)	(0.008)
Wage$_{2010}$ (log)	–0.006	0.050	0.017	0.021 *	0.029	0.070 **	0.047 ***	0.057 ***	0.018	0.031 **	0.004	–0.001	–0.004	–0.008	0.002	0.011
	(0.016)	(0.036)	(0.024)	(0.011)	(0.024)	(0.027)	(0.013)	(0.015)	(0.015)	(0.014)	(0.006)	(0.007)	(0.012)	(0.009)	(0.009)	(0.010)
Constant	–0.015	–0.075	0.000	–0.055	–0.090	–0.247 **	–0.179 ***	–0.108 ***	–0.054	–0.112 **	–0.032	–0.018	0.000	0.016	0.066 ***	–0.059
	(0.046)	(0.068)	(0.035)	(0.039)	(0.081)	(0.096)	(0.052)	(0.033)	(0.051)	(0.045)	(0.024)	(0.028)	(0.045)	(0.037)	(0.008)	(0.038)
Observations	80	84	92	95	111	95	166	109	83	42	117	108	40	56	82	84
R^2	0.66	0.486	0.541	0.618	0.357	0.735	0.551	0.815	0.557	0.669	0.826	0.772	0.511	0.937	0.745	0.818
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Sources: International Federation of Robotics; Cambridge University's Centre for Business Research (CBR); Organisation for Economic Co-operation and Development (OECD); World Input-Output Database; and IMF staff calculations.

Notes: Dependent variable = percentage change in employment growth averaged over 2010–14. High (low) output loss indicates that a country experienced above (below) median losses in output (as calculated in Annex 2.2.B). Measure of ALMP spending (as a percent of GDP) and EPL come from the OECD. Job churn rates are based on the calculations in Annex 2.2.C and dismissal regulation index is based on CBR leximetric measure of labor market policies. More flexible labor market includes countries that have above-median ALMP spending (% of GDP), above-median job churn rates, below-median dismissal regualtions as measured by CBR, and below-median EPL. Average change in robot density is the year-on-year change in robot density averaged over 2010–14. Control variables are 2010 value of capital services to wage bill (in logs) and wages per worker (in logs) in 2010. Regressions are weighted by 2010 within-country employment shares. Robust standard errors are in parentheses. ALMP = active labour market policies; EPL = employment protection legislation.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.