Online Appendix for Income-Driven Labor-Market Polarization

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A Tables and Figures

Table A.1: Correlation of Occupation Wage Bill over Total VA and Expenditure Elasticity

	Occupation Skill		
Year	Low	Middle	High
1980	0.57	-0.13	0.92
1990	0.51	-0.23	0.93
2000	0.52	-0.26	0.92
2016	0.51	-0.25	0.93

Notes: See discussion in Figure 2 in the main text for data sources. In terms of model parmaters this corresponds to the correlation between η_s and $\hat{\alpha}_{jst}$.

Table A.2: Robustness: Simulations by Subperiods

	Period 1980-2000						Period 2000-2016					
	Change Wage Bill Sh.			Change Employ. Sh.			Change Wage Bill Sh.			Change Employ. Sh.		
	Low	Mid.	High	Low	Mid.	High	Low	Mid.	High	Low	Mid.	High
Data (1980-2016)	0.0023	-0.116	0.113	0.005	-0.077	0.072	0.0185	-0.094	0.075	0.029	-0.088	0.059
Model	0.0023	-0.116	0.114	0.005	-0.079	0.074	0.0185	-0.094	0.075	0.023	-0.071	0.048
Model/Data (%)	100%	100%	100%	100%	102%	102%	100%	100%	100%	79%	81%	82%
Decomposition of Model:												
Shift	-0.0053	-0.067	0.083	-0.003	-0.054	0.058	0.0134	-0.072	0.06	0.008	-0.036	0.028
Share	0.0076	-0.049	0.031	0.008	-0.025	0.016	0.0051	-0.022	0.015	0.015	-0.035	0.02
Share/Model (%)	330%	42%	27%	169%	31%	22%	28%	23%	20%	65%	50%	42%
Contribution of Different Channels:												
Share, E	0.0126	0.0002	0.044	0.011	-0.033	0.022	0.0048	-0.003	0.023	0.004	-0.015	0.011
Share, Biased Tech.	-0.0021	-0.052	-0.019	0.0001	0.005	-0.005	-0.0027	-0.017	-0.02	0.008	-0.014	0.006
Share, E/Model (%)	548%	0%	39%	233%	42%	29%	26%	3%	31%	19%	21%	22%

Table A.3: Robustness: Including Trade Flows to our Baseline

	Change Wage Bill Sh.			Change Empl. Sh.		
	Low	Middle	High	Low	Middle	High
Data (1980-2016)	0.021	-0.209	0.188	0.034	-0.165	0.131
Model	0.021	-0.209	0.188	0.020	-0.146	0.126
Model/Data (%)	100%	100%	100%	59%	89%	97%
Decomposition of Model Outcomes:						
Shift	0.006	-0.151	0.130	-0.001	-0.087	0.088
Share	0.015	-0.058	0.058	0.022	-0.060	0.038
Share/Model (%)	73%	28%	31%	107%	39%	30%
Contribution of Different Channels to Share:						
Share, E	0.021	-0.006	0.073	0.020	-0.057	0.038
Share, Biased Tech.	-0.012	-0.057	-0.071	0.001	0.014	-0.015
Share, E/Model (%)	102%	3%	39%	99%	39%	30%

Table A.4: Robustness: CES Aggregator for Labor

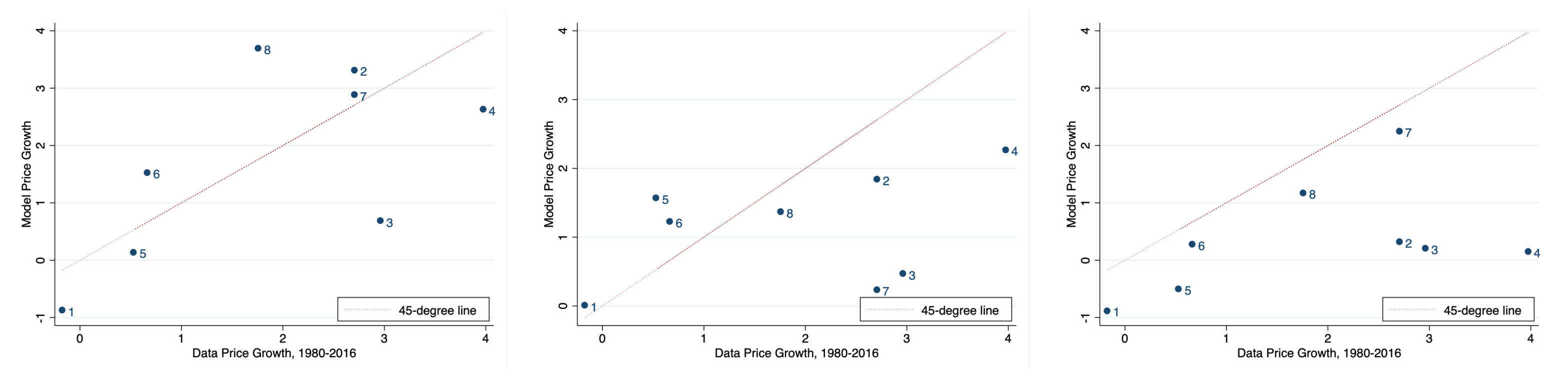
	Change Wage Bill Sh.			Change Empl. Sh.		
	Low	Middle	High	Low	Middle	High
Data (1980-2016)	0.021	-0.21	0.19	0.034	-0.16	0.13
Model	0.021	-0.21	0.19	0.024	-0.18	0.16
Model/Data (%)	100%	100%	100%	72%	110%	120%
Decomposition of Model Outcomes:						
Shift	0.006	-0.15	0.13	0.006	-0.12	0.12
Share	0.015	-0.06	0.06	0.019	-0.06	0.04
Share/Model (%)	73%	28%	31%	77%	33%	26%
Contribution of Different Channels to Share:						
Share, E	0.019	0.00	0.07	0.014	-0.05	0.03
Share, Biased Tech.	-0.008	-0.05	-0.06	0.003	0.01	-0.01
Share, E/Model (%)	91%	2%	35%	59%	27%	22%

Table A.5: Robustness: Only High-skill Workers Hold Capital

	Change Wage Bill Sh.			Change Empl. Sh.		
	Low	Middle	High	Low	Middle	High
Data (1980-2016)	0.021	-0.209	0.188	0.034	-0.165	0.131
Model	0.021	-0.209	0.188	0.028	-0.151	0.122
Model/Data (%)	100%	100%	100%	82%	91%	94%
Decomposition of Model Outcomes:						
Shift	0.006	-0.152	0.129	0.004	-0.089	0.085
Share	0.015	-0.057	0.059	0.024	-0.062	0.038
Share/Model (%)	74%	27%	31%	86%	41%	31%
Contribution of Different Channels to Share:						
Share, E	0.018	-0.001	0.063	0.016	-0.048	0.031
Share, Biased Tech.	-0.007	-0.056	-0.047	0.006	-0.001	-0.005
Share, E/Model (%)	87%	1%	33%	59%	32%	26%

Figure A.1: Sectoral Price Growth Data vs. Model, 1980-2016

(a) Full Model (b) Only E (c) Only Biased Technology



Legend: 1. Agriculture, Mining and Utilities, 2. Arts, Entertainment, Recreation and Food Services, 3. Government (excl. Health and Educ.), 4. Health and Education, 5. Manufacturing, 6. Retail, Wholesale and Transportation, 7. Construction, 8. Finance, Professional, Information and other services.

Table A.6: Robustness: Results for Relative Wages

		1980-2000		2000-2016		Trade		CES		K to High-Skill	
	Year	w_L/w_M	w_H/w_M	w_L/w_M	w_H/w_M	w_L/w_M	w_H/w_M	w_L/w_M	w_H/w_M	w_L/w_M	w_H/w_M
Data	1980	0.74	1.24	0.79	1.44	0.74	1.24	0.74	1.24	0.74	1.24
	2016	0.79	1.44	0.8	1.53	0.8	1.53	0.8	1.53	0.8	1.53
Model	1980	0.74	1.24	0.79	1.44	0.74	1.24	0.74	1.24	0.74	1.24
	2016	0.78	1.42	0.86	1.58	0.93	1.56	0.86	1.57	0.86	1.57
Contribution of Different Channels:											
Only E		0.77	1.29	0.8	1.46	0.79	1.33	0.78	1.3	0.78	1.31
Only Biased Tech.		0.76	1.38	0.84	1.55	0.88	1.45	0.81	1.48	0.81	1.47
Only E/Model (%)		63%	25%	21%	18%	26%	31%	38%	23%	38%	26%

Table A.7: Shift-Share Analysis of the Wage Bill Change for European Countries, 1980-2016

	Low-Skill				Middle-Skill				High-Skill			
	Total	Shift	Share	$\frac{\text{Share}}{\text{Total}}$	Total	Shift	Share	$\frac{\text{Share}}{\text{Total}}$	Total	Shift	Share	$\frac{\text{Share}}{\text{Total}}$
AUT	0.013	0.001	0.013	0.96	-0.17	-0.15	-0.03	0.15	0.16	0.11	0.05	0.29
GER	0.014	0.009	0.005	0.36	-0.19	-0.16	-0.03	0.16	0.18	0.14	0.03	0.19
ESP	0.022	-0.002	0.024	1.10	-0.18	-0.16	-0.02	0.12	0.16	0.10	0.06	0.35
FIN	0.016	0.002	0.014	0.88	-0.19	-0.12	-0.07	0.35	0.17	0.10	0.07	0.39
FRA	0.021	0.005	0.017	0.78	-0.19	-0.13	-0.06	0.31	0.17	0.13	0.04	0.23
ITA	0.017	0.003	0.015	0.85	-0.17	-0.10	-0.07	0.42	0.16	0.14	0.02	0.11
NLD	0.010	0.006	0.004	0.37	-0.18	-0.17	-0.01	0.06	0.17	0.12	0.04	0.27
UK	0.023	0.015	0.008	0.35	-0.21	-0.14	-0.08	0.36	0.19	0.15	0.04	0.19

Notes: Data for 2016 comes from EUKLEMS 2019 with occupation factors shares α^c_{js2016} computed from EU Labour Force Survey LFS micro dataset. Data for 1980 comes from EUKLEMS 2012, and occupation factor shares in 1980 are computed taking the occupation factor shares from 2016 and assuming that their growth rate is the same as that of the US. That is, $\alpha^c_{js1980} = \alpha_{js2016}/(1 + g^{US,1980-2016}_{\alpha_{js}})$.

Table A.8: Employment Shift-Share for European Countries, 1995-2016

	Low-Skill				Middle-Skill				High-Skill			
	Total	Shift	Share	$\frac{\text{Share}}{\text{Total}}$	Total	Shift	Share	$\frac{\text{Share}}{\text{Total}}$	Total	Shift	Share	$\frac{\text{Share}}{\text{Total}}$
AUT	0.010	-0.003	0.013	1.30	-0.10	-0.06	-0.05	0.46	0.09	0.06	0.03	0.37
BEL	0.036	0.014	0.023	0.62	-0.07	-0.01	-0.06	0.84	0.04	0.00	0.04	1.04
GER	0.005	-0.007	0.012	2.52	-0.09	-0.04	-0.05	0.56	0.09	0.05	0.04	0.45
DNK	0.003	-0.023	0.026	8.62	-0.11	-0.03	-0.08	0.70	0.11	0.06	0.05	0.48
EL	0.054	0.019	0.034	0.64	-0.02	0.07	-0.09	4.07	-0.03	-0.09	0.06	-1.82
ESP	0.038	0.001	0.037	0.98	-0.09	-0.01	-0.08	0.86	0.06	0.01	0.04	0.78
FRA	0.015	-0.014	0.029	1.87	-0.16	-0.12	-0.05	0.30	0.15	0.13	0.02	0.13
IE	0.022	0.006	0.016	0.74	-0.15	-0.08	-0.07	0.44	0.12	0.08	0.05	0.39
IT	0.011	-0.021	0.032	2.89	-0.12	-0.05	-0.06	0.54	0.11	0.08	0.03	0.30
LUX	-0.009	-0.019	0.010	-1.17	-0.20	-0.10	-0.10	0.49	0.21	0.12	0.09	0.43
NLD	0.009	-0.003	0.011	1.32	-0.07	-0.01	-0.06	0.85	0.06	0.01	0.05	0.79
PT	-0.006	-0.036	0.030	-4.78	-0.10	-0.02	-0.08	0.77	0.11	0.06	0.05	0.45
UK	0.023	-0.002	0.025	1.10	-0.10	-0.03	-0.07	0.66	0.08	0.04	0.04	0.53

Notes: Data on hours and wages from the EU LFS and EU SILC microdata sets. See description in Appendix B.3 for details.

Table A.9: Backtracking the US Economy, 1950-1980, Wage Bill and Employment Shares

	Change Wage Bill Sh.			Change Employ. Sh.		
	Low	Middle	High	Low	Middle	High
Data	-0.007	-0.106	0.113	-0.011	-0.078	0.089
Model	-0.007	-0.106	0.113	-0.006	-0.067	0.073
Model/Data(%)	100%	100%	100%	57%	86%	82%
Decomposition of Model Outcomes:						
Shift	-0.0161	-0.092	0.080	-0.018	-0.035	0.054
Share	0.0091	-0.014	0.034	0.012	-0.032	0.020
Share/Model(%)	-130%	13%	30%	-195%	47%	27%
Contribution of Different Channels to Share:						
Share, E	0.0252	0.009	0.045	0.024	-0.047	0.023
Share, biased tech	-0.0123	-0.048	-0.044	-0.007	0.019	-0.013
Share E/Model (%)	-360%	-8%	40%	-393%	71%	32%

Table A.10: Backtracking the US Economy, 1950-1980, Relative Wages

	Year	w_L/w_M	w_H/w_M
Data	1950	0.7	1.15
	1980	0.74	1.24
Model	1950	0.7	1.15
	1980	0.72	1.35
Contribution of Different Channels:			
Only E	1980	0.75	1.22
Only Biased Tech.	1980	0.67	1.27
Only E/Model (%)		250%	38%

Table A.11: Forecast of 2035 US Labor Market

		Wage Bill Share			Employment Shares			Relative Wages	
	Year	Low	Middle	High	Low	Middle	High	w_L/w_M	w_H/w_M
Data	2016	0.088	0.42	0.49	0.129	0.49	0.38	0.80	1.49
Model	2016	0.088	0.42	0.49	0.129	0.49	0.38	0.80	1.49
Model/Data (%)		100%	100%	100%	100%	100%	100%	100%	100%
Model (E shock)	2035	0.099	0.37	0.53	0.142	0.45	0.41	0.84	1.57
Model 2035/Data 2016 (%)		113%	89%	108%	110%	92%	106%	105%	105%

Notes: The table reports outcomes after simulating an E shock that generates half of the magnitude of the baseline increase in expenditure and Fisher price index.

B Data Description

In this section we briefly detail our data sources. We take it from previous work, and thus, we provide relatively brief descriptions and point the interested reader to the original papers for further details.

B.1 Labor-Market Outcomes

We follow Acemoglu and Autor (2011) in the construction of the baseline data on occupations, wages, and employment shares. Here we provide a brief overview and refer the reader to the original work by Acemoglu and Autor for the details. The data for employment comes from IPUMS USA and it includes the decennial censuses between 1980-2000 (with 10 years intervals) and annual data from the American Community Survey (ACS) between 2000-2016. The sample is restricted to individuals aged 16-64 who were employed in the previous year and are assigned to a known occupation (i.e., not n/a or unemployed). We further restrict the sample to exclude the top and bottom 5% of the hourly wage distribution. Wage data comes from the Current Population Survey (CPS) to compute wages per occupation. We follow Acemlogu and Autor on this choice because the data in the ACS has only intervals starting in 2007. Occupations and industries are classified based on the 1990 Census Bureau classification scheme, which gives a consistent classification for all sample years. These industries are mapped to the BEA industry classification through mutual mapping to the NAICS codes. For each BEA industry, we compute the share of individuals within each occupation.

Our occupation classification is also taken from Acemoglu and Autor (2011). They divide the 382 original occupations into 4 broader categories that are characterized by their skill level: (1) managerial, professional and technical occupations; (2) sales, clerical and administrative support occupations; (3) production, craft, repair and operative occupations; and (4) service occupations. The first group is characterized by high-skill occupations, the second and third groups are characterized by middle-skill occupations and the last group is characterized by low-skill occupations. They measure skill by the average hourly wage of individuals in the occupation in 1980 where the mean wage in each occupation is calculated using workers' hours of annual labor supply times the Census sampling weights.[1]

B.2 Construction of Household Value-added Consumption Data

We start from household expenditure from the Consumer Expenditure Survey (CEX). We use data from the 2000-2001 period for our baseline results, and report estimates for 2000-2006

[1]Our results on the negative correlation between occupation shares in middle-skill workers and income elasticity parameters are robust to decomposing middle-skill between groups (2) and (3).

as a robustness check.[2] We follow the procedure described in Aguiar and Bils (2015) to clean the data. We restrict our sample to urban households. We drop households if they report spending less than 100 dollars in food per individual in the household over a three month time span, they have negative total or food consumption expenditure, total income is reported incomplete, they have not responded to all (four quarterly) interviews, income is below 50% of minimum wage, or if they earn money but do not work. To mitigate measurement error concerns, we drop the top and bottom 5% households according to their total income (after taxes) and we winsorize top and bottom 5% sectoral expenditures.[3] The only difference from Aguiar and Bils is that we keep all households with age of the reference person above 18. This allows us to capture the consumption of the elderly.

We then follow the procedure described in Buera et al. (2015) and convert the final good expenditures reported in the CEX into value-added expenditures using the BEA's 2000 input-output tables.[4] We do so by matching the finest level of expenditure categories in the CEX (called UCCs) to each sector in the BEA table. We start from the correspondence used in Buera et al. (2015), which takes the BLS crosswalk from UCC codes to PCE lines (supplemented with some expert judgement).[5] Then, as in Buera et al. (2015), we use the BEA crosswalk from PCE (table 245) to industries in the Input/Output table. For the few cases in which there are UCCs from 2000-2006 missing from their original list, we make the assignment to PCE lines based on our judgement. We attach the correspondence in the authors' websites. Following Comin et al. (2015), we also use sectoral, regional urban price series provided by the BLS.[6]

The Input-Output BEA sector codes in the Input-Output table that correspond to our groupings are:

- 6 for Education and Health Care, plus state and local expenditures in health and education. More specifically, we add the lines in the detail of the BEA value-added table "U.Value Added by Industry" "State and local government educational services" (line 185) and "State and local government hospitals and health services" (line 186).

[2] We have experimented with different time frame periods between 1999 and 2007. The estimates are very stable across subsamples. Aguiar and Bils (2015) also report a similar finding in their estimated income elasticities.

[3] Total income after taxes is computed as in Aguiar and Bils (2015).

[4] We have also experimented using the detailed 2007 table, which contains over four hundred industries rather than sixty-nine. We obtain similar results. This exercise allows us to unpack industries such us "325 Chemical Products" into pharmaceuticals and the rest.

[5] This correspondence is available from the authors' website.

[6] When possible, we create a household-specific Stone price index for each sector from more disaggregated possible price series categories that belong to each sector. We then also convert final expenditure prices to value-added prices by assuming a Cobb-Douglas production function and perfect competition, such that the log price of a sector is the input-share weighted mean of log-prices.

The BEA Table does not provide a break-down for Federal expenditure in Education and Health, and we do not include it.

- 7 for Arts, Entertainment, Recreation and Food Services.
- G for Government (excluding the lines corresponding to state and local education and health care value added mentioned above).
- FIRE, PROF, 51, 81 for Finance, Professional, Information and other services (excluding gov't), excluding real estate (line 129, which includes housing and other real estate) in the BEA value-added table U.Value Added by Industry.
- 22, 23, 31G for Manufacturing, Mining and Utilities.
- 42, 44RT, 48T for Retail, Wholesale Trade and Transportation.
- 21 for Construction and Real Estate (line 129 in BEA Table U.Value Added by Industry).
- 11 for Agriculture.

B.2.1 Reduced Form Exercise: Comparison with Aguiar and Bils (2015)

We want to mention two important differences from Aguiar and Bils (2015). First, we discuss the mapping of UCCs to Health expenditures, which is different in Buera et al. (2015) and Aguiar and Bils (2015). Second, we discuss the role of the approximation to the left-hand-side that Aguiar and Bils take as baseline.

Mapping of Health Expenditures Aguiar and Bils (2015) take the expenditure groupings for health and education from the CEX groupings. Instead, as we have discussed, we follow Buera et al. (2015) and map each expenditure category at the finest level of reporting in the CEX (called UCC) to different PCE lines and, ultimately, different NIPA lines. This does not make a difference for most of expenditure categories (e.g., education), but it makes a difference for health.

Health services in our data are composed of the categories that are mapped to lines starting with 62 in the BEA Input Output table (or lines 60 to 67 in NIPA table 2.4.5). These UCCs are: 340906 Care for elderly, invalids, handicapped, etc. (in the home), 560110 Physicians' services, 560210 Dental services, 560330 Lab tests, x-rays, 560400 Service by professionals other than physicians, 570110 Hospital room (thru 2005 Q1), 570111 Hospital room and service (introduced 2005 Q2), 570210 Hospital service other than room (thru 2005

Q1), 570220 Care in convalescent or nursing home, 570230 Other medical care services, 570230 Other medical care services, 570240 Medical care incl. in homeowners expenses, 570901 Rental of medical equipment, 570903 Rental of supportive/convalescent equipment, 571230 Other medical care services, 572230 Other medical care services.

Instead, Aguiar and Bils follow the CEX grouping for "Health." This grouping contains UCCs from 540000 to 580902. This grouping includes expenditures in prescription drugs and medical supplies (UCC's 540000-550340, 570901, 570903) and Health Insurance (UCCs 580110-580902) as part of "Health." Instead, we match the UCC's corresponding prescription drugs to "Pharmaceutical and other medical products" (lines 40 and 41 in NIPA table 2.4.5) and health insurance to "Health Insurance" (line 93 in NIPA table 2.4.5). We are also including UCC "340906 Home health care" as a health service (which is not included in Aguiar and Bils).

Approximation of the log-ratio in the left-hand-side of Equation (19) Aguiar and Bils (2015) present their theory and justification for their estimating equation by having on the left-hand side of the regression $\ln(x_{hst}/\bar{x}_{st})$ (Equation 4 in their paper). However, in their empirical analysis, they substitute $\ln(x_{hst}/\bar{x}_{st})$ by its first-order approximation around $\bar{x}_{st}$, $(x_{hst} - \bar{x}_{st})/\bar{x}_{st}$. They justify their choice because the presence of zeros in the data (e.g., for education alone zeros account for around 50% of the observations). However, we do not have zeros in our data because it is (1) more aggregated (eight sectors rather than twenty) and (2) the input-output matrix makes it so that there is always some (albeit small) consumption of all eight industries (e.g., education and health is an input to other sectors and thus all households have positive value-added consumption of it).

Since we do not find a problem of zeroes arising in our value-added measure of consumption, we proceed with the estimation of the exact equation that has on the left-hand-side $\ln(x_{hst}/\bar{x}_{st})$. If we run our regression with the same approximation in the left-hand-side as Aguiar and Bils, we find similar coefficients. However, for the categories in which there is more dispersion in expenditures (which tend to be the more expenditure-elastic categories), this first-order approximation becomes worse and results in smaller estimates of the expenditure elasticity. This is especially true for Health and Education, in which we find that the coefficient can drop by almost 30%.

B.2.2 Demand Estimation: Robustness Checks

Our baseline estimation uses imputed consumption value-added for health, education and finance. In column (2) of Table B.1 we report the estimates that we obtain without the imputation. The key difference is that the nonhomotheticity parameter for Education and

Health Care increases from 1.80 to 2.08. This implies an increase from 1.59 to 1.75 in the implied expenditure elasticity of the average household. The rest of the parameters are very similar. In particular, the imputation for Finance is not quantitatively important, with the parameter estimate changing from 1.39 in our baseline to 1.36. Columns (3) and (4) of Table B.1 show that the estimated parameters are similar to our baseline if we remove year-round fixed effects and use the within year variation to also identify expenditure elasticities, or if we extend our sample period from 2000 to 2006.[7]

Details on the Imputation Procedure We start discussing the imputation of education expenditures. We use expenditure per pupil at the school district-level for years 2000-2001 from the Common Core Database. For the median household income at the county level, we use the IPUMS-ACS. For counties with missing median household income, we impute the state median household income. We merge school districts to counties and regress log-expenditure per pupil on log household income with state fixed effects and a time trend. We then use the predicted values from the regression to impute the value of education of a student in K-12. We use the family files from the CEX to find out the number of children in each household in K-12 age. We impute the expenditure according to the number of children in K-12 age *if* the household does not report paying any elementary or high-school tuition. We impute it to UCC code 670210 "elementary and high-school tuition."

For Medicare and Medicaid expenditures we follow an analogous procedure. We use data in the Dartmouth Atlas on average expenditure per patient by hospital referral region (these data were generously shared and described to us by Douglas and Betsy Staiger and Jonathan Skinner). We then merge these information to county household average income. Since hospital referral regions do not coincide with counties, we use population in the referral region and county as a weight for computing the average expenditure per county. After this step, we proceed with the imputation in the same way as for education. Once we have a measure of expenditures per person in a given county, we use information in the CEX on the number of household members under Medicaid and Medicare to make the imputation. In this case, we assign the expenditure to UCC 580901, which corresponds to "Medicare payments" (there is no analogous Medicaid payments in the CEX interview files until 2017).

Finally, we also explore the role of financial services that may potentially be underreported in the CEX. In particular, expenses in fund management that are subtracted from the fund payout appear to be missing in the CEX. For this reason, we proceed by assuming an expense ratio of 90 basis points over the year in all funds owned by a household and we evenly spread

[7]The reason why we start in 2000 and not earlier is that this is the start for disaggregated sectoral city price indices from the BLS.

Table B.1: Estimated Demand and Income Elasticities: Robustness Checks

	Demand Parameters				Red. Form	
	(1)	(2)	(3)	(4)	(5)	(6)
Nonhomotheticity Parameters ε_s					*Inc. Elast.* η_s	
Education and Health Care	1.80	2.08	1.93	2.15	1.59	1.75
	(0.07)	(0.13)	(0.06)	(0.14)	(0.06)	(0.05)
Arts, Entertainment, Recreation and Food Services	1.39	1.36	1.42	1.51	1.31	1.25
	(0.03)	(0.04)	(0.03)	(0.06)	(0.03)	(0.03)
Finance, Professional, Information, other services (excl. gov't)	1.26	1.25	1.26	1.21	1.29	1.25
	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.01)
Government[1]	1.00	1.00	1.00	1.00	1.08	1.07
	(-)	(-)	(-)	(-)	(0.01)	(0.01)
Manufacturing	0.69	0.71	0.61	0.67	0.91	0.92
	(0.03)	(0.03)	(0.03)	(0.04)	(0.01)	(0.01)
Retail, Wholesale Trade and Transportation	0.61	0.66	0.55	0.61	0.87	0.88
	(0.03)	(0.04)	(0.03)	(0.05)	(0.01)	(0.01)
Construction	0.48	0.49	0.44	0.47	0.80	0.80
	(0.04)	(0.06)	(0.04)	(0.06)	(0.02)	(0.02)
Agriculture	0.30	0.35	.21 0	0.23	0.65	0.66
	(0.06)	(0.08)	(0.05)	(0.09)	(0.02)	(0.01)
Elasticity of Substitution σ	0.45	0.43	0.53	0.58		
	(0.05)	(0.08)	(0.04)	(0.06)		
Region & Round FE	Y	Y	N	N	Y	Y
Region & Year FE	Y	Y	Y	Y	Y	Y
Sample Years	00-01	00-01	00-01	00-06	00-01	00-01
Imputed Expenditures	Y	N	Y	Y	Y	N

Notes: Standard errors clustered at the household level in parentheses. [1]: The Government nonhomotheticity parameter is normalized to 1.

the expense over the 4 quarters (French, 2008).[8] These funds are pension funds (including amount of money placed in a self-employed retirement plan) and the estimated market value of all stocks, bonds, mutual funds, and others such as securities. These expenses are imputed in UCC 710110 "Finance charges excluding mortgage and vehicle."

[8]The Investment Company Insitute and Lipper report that the average expense ratios for bond funds in 2000 were 76 basis points, 89 for hybrid funds and 99 for equity funds. We take 90 which is a rough average between the three. In their study, they also document a substantial decline in these expense ratios over time. In 2015 they were 54, 77 and 68.

B.3 European Countries Data

We use microdata from the LFS and SILC in order to estimate the wages, hours worked and implied sector intensities $\{\alpha_{jstc}\}_{j=\{L,M,H\},s\in\mathcal{S},c\in C}$ (where C denotes the set of countries). Specifically, we use the LFS data to calculate the hours worked by each skill level in each sector. In order to do so, we map the NACE Rev 1.1 and 2 to our sector classification using the NACE-NAICS correspondence tables provided by Eurostat. For the occupation classification, we keep the same classification as high-, middle- and low-skill as for the US. We focus on individuals that are employed and are not family workers between the ages 16-64. Next, we use the SILC data to calculate the mean wage for each skill type across all industries. We use the same sample restrictions and skill classification. We calculate the wage per hour by dividing the monthly or annual labor income, depending on data availability, by the hours worked in the relevant period. For this purpose we use usual weekly hours worked, multiplied by number of months worked in a year and assuming individuals worked 4 weeks in each month since these data are not directly provided. To make sure the annual labor income was earned while working in the current occupation, we further restrict the sample to individuals that did not switch work since the previous year.

For total labor compensation share and value-added share in each sector we use EU KLEMS data. Since there is no single version of EU KLEMS that spans the 1980 and 2016 (except for France), we merge the EU KLEMS 2012 and 2019 versions. We compute these ratios using sectoral value added, total value added, and total labor compensation.[9] Finally, we aggregate the sectors (which are originally given in different revisions of the ISIC codes) into the same 8 main sectors as we do for the US baseline. In this case, we can impute *all* public expenditures in health and education.

C Detailed Derivations of Production and Demand for Section 4

C.1 Production

A representative firm in each sector produces final output according to

$$Y_{st} = A_{st} K_{st}^{1-\beta_{st}} \left(\prod_{j\in\{L,M,H\}} \tilde{X}_{jst}^{\alpha_{jst}} \right)^{\beta_{st}}, \qquad \text{where} \quad \sum_{j\in\{L,M,H\}} \alpha_{jst} = 1, \quad \beta_{st} \in (0,1), \tag{1}$$

[9] We use the variable LAB, which is present in both datasets.

and $\tilde{X}_{jst}$ denotes the number of efficiency units of labor employed in occupation j sector s, and year t. This setting is identical to that of Section 2.1, except that the production function is expressed in terms of efficiency units rather than total hours. Cost minimization from the representative firm implies that

$$\tilde{w}_{jt}\tilde{X}_{jst} = \beta_{st}\alpha_{jst}p_{st}Y_{st}, \tag{2}$$

$$(r_t+\delta)K_{st} = (1-\beta_{st})\, p_{st}Y_{st}, \tag{3}$$

where $\tilde{w}_{jt}$ denotes wage per efficiency unit, and the rental rate is equal to the interest rate, r_t, plus the depreciation rate δ. Aggregating across labor inputs within the same sector, we find that β_{st} corresponds to the labor share of that sector,

$$\beta_{st} = \frac{\sum\limits_{j\in\{L,M,H\}} \tilde{w}_{jt}\tilde{X}_{jst}}{p_{st}Y_{st}}. \tag{4}$$

In a competitive equilibrium, the price of the sectoral output coincides with the unit cost of production,

$$p_{st} = A_{st}^{-1}\left(\frac{\prod_{j=\{L,M,H\}}\left(\frac{\tilde{w}_{jt}}{\alpha_{jst}}\right)^{\alpha_{jst}}}{\beta_{st}}\right)^{\beta_{st}}\left(\frac{r_t+\delta}{1-\beta_{st}}\right)^{1-\beta_{st}}. \tag{5}$$

Next, we use the first order condition across sectors to compute total factor payments. Aggregating efficiency units of the same occupation across sectors and introducing the notation $\tilde{X}_{jt} \equiv \sum\limits_{s=1}^{S}\tilde{X}_{jst}$, we find that the total compensation for workers employed in occupation j is

$$\tilde{w}_{jt}\tilde{X}_{jt} = \sum_{s=1}^{S}\hat{\alpha}_{jst}p_{st}Y_{st}, \tag{6}$$

where $\hat{\alpha}_{jst} \equiv \beta_{st}\alpha_{jst}$. Similarly, the total payments to capital owners are

$$(r_t+\delta)K_t = \sum_{s=1}^{S}(1-\beta_{st})\, p_{st}Y_{st}. \tag{7}$$

C.2 Household preferences, endowments and demographics

Each household maximizes utility U_{ht} defined by the nonhomothetic CES aggregator

$$\sum_{s\in\mathcal{S}}\left(U_{ht}^{\varepsilon_s}\zeta_s\right)^{\frac{1}{\sigma}} c_{hst}^{\frac{\sigma-1}{\sigma}} = 1, \tag{8}$$

subject to the household budget constraint $E_{ht} \geq \sum_s p_{st} c_{hst}$. Household's h optimal demand for good s is

$$c_{hst} = \zeta_s \left(\frac{E_{ht}}{p_{st}} \right)^{\sigma} U_{ht}^{\varepsilon_s}, \tag{9}$$

and the associated expenditure function, $E_{ht}^{1-\sigma} = \sum_{s \in \mathcal{S}} \zeta_s U_{ht}^{\varepsilon_s} p_{st}^{1-\sigma}$.

As we have discussed in Section 3.1, we cardinalize preferences normalizing one taste parameter $\zeta_s = 1$ and one income elasticity parameter $\varepsilon_s = 1$ for some s. This cardinalization defines a household-specific real consumption index $C_{ht} \equiv \frac{E_{ht}}{P_{ht}}$ and corresponding price index P_{ht}

$$P_{ht} = \left[\sum_{s \in \mathcal{S}} \left(\zeta_s p_{st}^{1-\sigma} \right)^{\theta_s} \left(x_{hst} E_{ht}^{1-\sigma} \right)^{1-\theta_s} \right]^{\frac{1}{1-\sigma}}, \tag{10}$$

where $x_{hst} \equiv p_{st} c_{hst} / E_{ht}$ denotes the expenditure share in sector s, and $\theta_s \equiv (1-\sigma)/\varepsilon_s$. Note that given knowledge of the demand parameters $\{\zeta_s, \varepsilon_s, \sigma\}_{s \in \mathcal{S}}$, sectoral prices $\{p_{st}\}_{s \in \mathcal{S}}$, and household expenditures and expenditure shares, $\{x_{hst}, E_{ht}\}$, we can use Equation (10) to obtain the household-specific price index P_{ht}. Then, the aggregate demand for sectoral output s can be obtained by integrating over the demand of all households,

$$C_{st} = \int_0^1 \zeta_s E_{ht}^{\sigma + \varepsilon_s} p_{st}^{-\sigma} P_{ht}^{-\varepsilon_s} dh. \tag{11}$$

D Calibration of Model Parameters

To calibrate our model parameters for 1980, we need to specify the values of $\{\zeta_s, \varepsilon_s, \sigma\}_{s \in \mathcal{S}}$, δ, sectoral technologies $\{\alpha_{s1980}, \beta_{s1980}, A_{s1980}\}_{s \in \mathcal{S}}$, initial capital stock per capita K_{1980},[10] and the distribution of productivity parameters in each occupation $\{\eta_j\}_{j=\{L,M,H\}}$.

First, we set the values of σ and $\{\varepsilon_s\}_{s \in \mathcal{S}}$ to the estimates we obtained in Table 3. Second, we set the values of $\{\alpha_{sj1980}, \beta_{s1980}\}_{s \in \mathcal{S}}$ to match the share of each occupation in the sectoral wage bill and the wage-bill share in sectoral value added for all sectors

$$\beta_{s1980} = \frac{\sum_{j \in \{L,M,H\}} w_{j1980} X_{js1980}}{VA_{s1980}}, \tag{12}$$

and

$$\alpha_{js1980} = \frac{w_{j1980} X_{js1980}}{\sum_{j' \in \{L,M,H\}} w_{j'1980} X_{j's1980}}. \tag{13}$$

[10]Since the production functions are homogeneous of degree one, we define all aggregate and sectoral variables in per capita terms.

Third, we set the depreciation rate δ to 10% per year. Given the interest rate, which we measure by the lending rate from FRED,[11] sectoral value added and the capital shares in each sector, we calculate the aggregate stock of capital as

$$K_{1980} = \sum_{s \in S} K_{s1980} = \frac{\sum_{s \in S}(1-\beta_{s1980})VA_{s1980}}{r_{1980}+\delta}. \tag{14}$$

The fourth step consists in calibrating the parameters in the distribution of efficiency units $\{\eta_j\}_{j=\{L,M,H\}}$. We assume that efficiency units are drawn from independently distributed lognormal distributions with mean and variance of the log-efficiency unit denoted by $\{\mu_j, \chi_j\}_{j=\{L,M,H\}}$. Since the definition of an efficiency unit of each type of labor (L, M and H) is indeterminate, the average level of efficiency units in each occupation μ_j is a free parameter that can be normalized without loss of generality. Equivalently, given the level of value added across sectors and the factor intensities, a renormalization of μ_j by a factor λ will result in a reduction in the wage per efficiency unit of occupation j, $\tilde{w}_j$, by the same amount.[12] Building on this property, we set the values of the mean of the efficiency unit parameters $\{\mu_j\}_{j=\{L,M,H\}}$ to a common level μ_{1980}. We discuss below how we calibrate this value.

The wage-bill share of occupation j in the total wage bill is given by the right hand side of Equation (16)

$$\frac{WB^{data}_{j1980}}{\sum_{j'} WB^{data}_{j'1980}} = \frac{\frac{\tilde{w}_{j1980}}{\tilde{w}_{L1980}} \int_0^\infty f_j(y) \prod_{i \neq j} F_i\left(\frac{w_j}{w_i} y\right) dy}{\sum_{j'} \frac{\tilde{w}_{j'1980}}{\tilde{w}_{L1980}} \int_0^\infty f_j(y) \prod_{i \neq j} F_i\left(\frac{\tilde{w}_{j'}}{w_i} y\right) dy}, \tag{16}$$

where f_i and F_i denote the pdf and the cdf of a lognormal distribution. These functions are fully characterized by $\{\mu_j, \chi_j\}_{j=\{L,M,H\}}$. Given those, the RHS of (16) depends only on the relative wages per efficiency unit. This observation implies that for any given set of parameters that characterize the distribution of productivities across occupations, the requirement that the model matches the observed relative wage bills in 1980 uniquely pins down the equilibrium relative wage per efficiency unit ($\tilde{w}_{j1980}/\tilde{w}_{L1980}$). The next step is to use the observed relative wage per hour in 1980 to calibrate the variance of the distribution

[11] The interest rate values in the baseline exercise are 15% and 3.5% for 1980 and 2016, respectively. The interest values for the extensions are 4.8% and 9.2% for 1950 and 2000, respectively.

[12] To see this, note that the demand for efficiency units of occupation j is

$$\tilde{X}_{jt}\tilde{w}_{jt} = \sum_s \hat{\alpha}_{jst} VA_{st}. \tag{15}$$

Hence, for given factor intensity and sectoral value added, an increase in μ_j increases $\tilde{X}_{jt}$, but leaves unchanged the wage bill accrued by occupation j, leading to an inversely proportional change in $\tilde{w}_{jt}$.

of productivity across occupations. Given $\{\tilde{w}_{jt}/\tilde{w}_{Lt}\}_{j=\{L,M\}}$and $\{\mu_j\}_{j=\{L,M,H\}}$, the average wage per hour in occupation j relative to occupation L can be expressed as indicated in the far RHS expression of (17):

$$\frac{w_{j1980}^{data}}{w_{L1980}^{data}} = \frac{\frac{\tilde{w}_{j1980}\tilde{X}_{j1980}}{\pi_{j1980}}}{\frac{\tilde{w}_{L1980}\tilde{X}_{L1980}}{\pi_{L1980}}} = \frac{\tilde{w}_{j1980}}{\tilde{w}_{L1980}} \frac{\frac{\tilde{X}_{j1980}}{\pi_{j1980}}}{\frac{\tilde{X}_{L1980}}{\pi_{L1980}}}. \tag{17}$$

The first factor in the far RHS expression is the relative wage per efficiency unit which, given the distribution of the wage bill across occupations and $\{\mu_j\}_{j=\{L,M,H\}}$, only depends on the variance of productivity $\{\chi_j\}_{j=\{L,M,H\}}$. The second term is the average number of efficiency units per worker in occupation j relative to L. For the case of H, in our model this is equal to

$$\frac{\tilde{X}_{H1980}}{\pi_{H1980}} = \frac{\int_{y\in\mathcal{Y}} yF_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \ldots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right) dy}{\int_{y\in\mathcal{Y}} F_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \ldots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right) dy}, \tag{18}$$

where F_H denotes the partial derivative with respect to H-draws of the joint cumulative distribution.[13] The expression for other skill levels is analogous. Given $\{\tilde{w}_{jt}/\tilde{w}_{Lt}\}_{j=\{L,M,H\}}$and $\{\mu_j\}_{j=\{L,M,H\}}$, this term also depends only on $\{\chi_j\}_{j=\{L,M,H\}}$. By requiring that the model matches the average wage per hour of occupations M and H relative to L observed in 1980, we can pin down two of the three variances of productivity across occupations. In other words, we can match the observed wage bill distribution and relative wages per hour by setting the relative variance of productivity across occupations. Accordingly, we normalize

[13] Let $F(\eta_H, \eta_M, \eta_L)$ be the CDF of the joint distribution of the efficiency units across occupations. The density of a household choosing occupation H is

$$F_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \ldots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right), \tag{19}$$

where $F_H = \frac{\partial F(\eta_H,\eta_M,\eta_L)}{\partial \eta_H}$. Thus, the share of households choosing occupation H is

$$\pi_H = \int_{y\in\mathcal{Y}} F_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \ldots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right) dy \tag{20}$$

where $\mathcal{Y}$ denotes the support of the distribution for η_H. The supply of efficiency units in occupation H is

$$\tilde{X}_{jt} = \int_{y\in\mathcal{Y}} yF_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \ldots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right) dy \tag{21}$$

and the wage bill accrued by workers in occupation H is

$$\tilde{w}_H\tilde{X}_{jt} = \tilde{w}_H \int_{y\in\mathcal{Y}} yF_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \ldots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right) dy \tag{22}$$

Analogous expressions to (20), (21), and (22) hold for the other occupations.

$\chi_L = 1$ and set $\{\sigma_j\}_{j=\{M,H\}}$ to match the 1980 relative wage per hour. Note that, since we match the relative wage per hour and the distribution of wage bills across occupations, automatically we also match the distribution of hours across occupations.

Fifth, given the wage per efficiency unit for each occupation, the rental cost of capital and the factor shares, we can calibrate the sectoral TFP levels A_{s1980} to match the sectoral prices in 1980 which in the model are given by equation (5). Note, however, that we have not yet determined how to pin down the level of efficiency wages for low-skill occupations $\tilde{w}_{L1980}$. We will discuss this in step seven of the calibration below.

The sixth step in our calibration procedure is to set the values of the taste parameters $\{\zeta_s\}_{s=1}^{S}$ to match the 1980 sectoral shares in value added. To do this, note first that household's h total income is equal to its labor income plus its capital income

$$E_{1980}^h = \max_{j \in \{L,M,H\}} \{\tilde{w}_{j1980}\eta_{j1980}^h\} + r_{1980}K_{1980}. \tag{23}$$

Given the distribution of E_{1980}^h, the share of sector s value added in aggregate value added is

$$x_{s1980} = \frac{p_{s1980}Y_{s1980}}{E_{1980}} = \frac{p_{s1980}\int_h c_{s1980}^h(\{\zeta_s\}, E_{1980}^h, \{p_{s1980}\})dh}{E_{1980}} = \frac{p_{s1980}^{1-\sigma}\int_h \zeta_s \left(E_{1980}^h\right)^{\sigma+\varepsilon_s} P_{1980}^h dh}{E_{1980}} \tag{24}$$

where $c_{s1980}^h(.)$ is household h real consumption of sector s, and P_{1980}^h is the household-level price index for 1980.[14] Given aggregate expenditure E_{1980}, we set $\{\zeta_s\}_{s=1}^{S}$ so that x_{s1980} matches the BEA shares of sectoral value added in 1980.

The seventh step consists in setting μ_{1980} so that the level of aggregate expenditure per capita in the model (26) matches the BEA level of aggregate nominal value added in 1980,

$$E_{1980} = \int_h \tilde{w}^h \tilde{X}^h dh + (r_{1980} + \delta)K_{1980}. \tag{26}$$

Note that, by increasing μ_{2016}, we also change the level of efficiency wage $\tilde{w}_{Lt}$. As we discussed in detail in footnote 12, conditional on the total wage bill of low-skill occupations, there is a one-to-one relationship between the level of efficiency units supplied $\tilde{X}_{L2016}$ and the efficency wage $\tilde{w}_{Lt}$.

To calibrate the model for 2016, we assume that the preference parameters $\{\zeta_s, \varepsilon_s, \sigma\}_{s\in\mathcal{S}}$,

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[14]The corresponding expression is

$$P_{1980}^h = \left[\sum_{s\in S} \left(\zeta_s p_{s1980}^{1-\sigma}\right)^{\chi_s} \left(x_{s1980}^h \left(E_{1980}^h\right)^{1-\sigma}\right)^{1-\chi_s}\right]^{\frac{1}{1-\sigma}} \tag{25}$$

where x_{s1980}^h is the share of sector s in its expenditure the depreciation rate δ, and the dispersion in the distributions of occupational productivities $\{\sigma_j\}_{j=\{L,M,H\}}$ do not vary from their 1980 values. We allow changes in the values of the factor intensities, $\{\alpha_{sj2016}, \beta_{s2016}\}$, the (constant) average productivity in each occupation μ, the sectoral, $\{A_{s2016}\}_{s\in\mathcal{S}}$, and aggregate, A_{2016}, TFP levels, and the capital stock per capita, K_{2016}.

As in 1980, we recalibrate the values of the factor intensity parameters, $\{\alpha_{sj2016}, \beta_{s2016}\}$, to match the share of each occupation in the sectoral wage bill and the wage-bill share in value added for all sectors

$$\beta_{s2016} = \frac{\sum_{j\in\{L,M,H\}} w_{j2016}X_{js2016}}{VA_{s2016}}, \tag{27}$$

and

$$\alpha_{js2016} = \frac{w_{j2016}X_{js2016}}{\sum_{j'\in\{L,M,H\}} w_{j'2016}X_{j's2016}}. \tag{28}$$

Using the information on the rental rate of capital, labor shares and value-added shares across sectors, the aggregate nominal value added per capita in 1980, and the increase in per capita expenditure from 1980 to 2016, we can calibrate the aggregate level of capital per capita in 2016 as:

$$K_{2016} = \sum_{s\in\mathcal{S}} K_{s2016} = \frac{\sum_s (1-\beta_{s2016})\left(\frac{VA_{s2016}}{VA_{2016}}\right)}{r_{2016}+\delta}\left(VA_{1980}\frac{E_{2016}}{E_{1980}}\right). \tag{29}$$

Note that, if as in our model, aggregate personal expenditure and value added grew at the same rate from 1980 to 2016, $(r_{2016}+\delta)K_{2016}$ would match the level of gross capital income per capita in the data. However, since the growth of nominal value added does not exactly coincide with the growth in personal consumption expenditure, our calibration will not perfectly match that. It will however match the sectoral distribution of capital (i.e., K_{s2016}/K_{2016}), as this does not depend on the relative growth of value added and expenditures.

Let $\hat{A}_{s2016} = A_{s2016}/A_{2016}$ be the relative TFP level in sector s. We calibrate simultaneously $\left\{\hat{A}_{s2016}\right\}_s$, A_{2016}, and μ_{2016} so that we match the 2016 sectoral shares on nominal value added $\{x_{s2016}\}_s$, the growth in aggregate expenditures per capita, and in the Fisher price index of personal consumption expenditures from 1980 to 2016. Next we present the equations that we use to determine the values at which we set these model parameters to match the targeted moments in the data. Given the distribution of occupational productivities (including μ_{2016}), and the level of capital per capita K_{2016}, household h income is

$$E^h_{2016} = \max_{j\in\{L,M,H\}}\{\tilde{w}_{j2016}\tilde{X}^h_{j2016}\} + r_{2016}K_{2016}. \tag{30}$$

Given aggregate expenditure per capita (E_{2016}), the share of sector s in aggregate expenditure (or nominal value added) is

$$x_{s2016} = \frac{p_{s2016} \int_h c_s^h(\{\zeta_s\}_s, E_{2016}^h, \{p_{s2016}\}_s) dh}{E_{2016}} \tag{31}$$

where the function c_s^h is defined in equation 24. Note that sectoral prices p_{s2016} are given by

$$p_{s2016} = \left(A_{2016}\hat{A}_{s2016}\right)^{-1} \left(\prod_{j=\{L,M,H\}} \left(\frac{\widetilde{w}_{j2016}}{\hat{\alpha}_{js2016}}\right)^{\hat{\alpha}_{js2016}}\right) \left(\frac{r_{2016}+\delta}{1-\beta_{s2016}}\right)^{1-\beta_{s2016}} \tag{32}$$

and the Fisher price deflator from 1980 to 2016 is

$$F_{2016} = \sqrt{\left(\frac{\sum_s P_{2016}\cdot Y_{1980}}{\sum_s P_{1980}\cdot Y_{1980}}\right)\left(\frac{\sum_s P_{2016}\cdot Y_{2016}}{\sum_s P_{1980}\cdot Y_{2016}}\right)}. \tag{33}$$

It follows from equations (30), (31) and (32) that, given factor inputs and shares, capital per capita and the aggregate TFP level, relative sectoral TFP pins down the sectoral shares in value added. Additionally, given the values of these variables plus the sectoral shares in value added for 1980 and 2016, the mean log-level of productivity in each of the three occupations μ_{2016}, or equivalently the level of the wage per efficiency units for low skilled occupation ($\tilde{w}_{L2016}$), can be pinned down so that the model-implied Fisher price index (33) matches the data. Finally, the overall growth of the economy from 1980 to 2016 is determined by the calibration of the level of aggregate TFP in 2016. We set this parameter so that the growth in personal consumption expenditures per capita in our model (34) matches the value observed in the data as reported by the BEA,

$$\frac{E_{2016}}{E_{1980}} = \frac{\int_h E_{2016}^h dh}{VA_{1980}}. \tag{34}$$

E Construction of the Value-Added Trade Data

We use the consolidated Input-Output table for the US from the World Input Output Database (available at http://www.wiod.org) to compute the share of value-added relative to total gross inputs by sector, α_s, $s = 1, \ldots, S$. We compute the average across all years available for the 2013 WIOD release (1995-2011).[15] Armed with the sectoral value-added

[15]We have checked that there are no significant trends in value-added shares for agriculture and manufacturing. If we regress value-added shares on year and a constant we find a non-significant coefficient on time for agriculture and a significant but economically very small coefficient of 0.18% for manufacturing (this

shares $\{\alpha_s\}_{s\in\mathcal{S}}$, we compute the value-added content of net exports by sector and year. We use COMTRADE data on sectoral trade flows for 1980 and 2016 (since the WIOD input output table does not span a sufficiently long horizon). We also map sectoral trade flows and value-added shares into our eight sectors. The only sectors with positive trade flows are: Agriculture, Mining, and Utilities and Manufacturing.

Note that we are imputing the US value-added shares to US imports (in addition to exports). The reason is that we are interested in understanding the effects of trade diversion on the US economy. Thus, a reduction in demand to US producers due to increased imports translates into a decline in labor demand of US producers. In order to capture this effect appropriately we need to use US value-added shares for imports.

Calibration Details To account for international trade we calibrate $\{\zeta_s\}$ and the sector specific TFP terms. We calibrate $\{\zeta_s\}$ so that the domestic aggregate demand in the model matches the domestic VA shares in each sector observed in 1980. We calibrate the sector specific TFP terms that so that the domestic demand augmented by the factor $(1-\tau_{s1980})^{-1}$ as discussed in equation (28) matches the total VA share in each sector observed in 1980. The calibration of the distribution parameters of efficiency units are done to match relative average wages and employment shares. They are done as in the baseline calibration since this part is independent from the trade module. In our main exercise for 2016 we augment each sector specific TFP term by a factor of $(1-\tau_{s,2016})$, as well as adjust factor and labor intensity parameters α_{st}, β_{st} and then re-calibrate the change in μ_t and aggregate TFP to match the increase in nominal personal consumption expenditures per capita and the price index.

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