Online Appendix: Intermediate Good Sourcing, Wages and Inequality: From Theory to Evidence

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Part I

Empirical Appendix

I.1 Labor Market Frictions and Trade Flows

I construct an index of labor market rigidity from legal regulations at the country-year level using data on labor market laws collected by the World Bank, as part of their Cost of Doing Business dataset. The data spans 2006-2011 which is then matched to the U.S. Census provided related party trade data. The index of labor market frictions is constructed as a linear combination of five variables measuring the rigidity of employment conditions within countries. These variables include days of paid annual leave, weeks of severance pay required when firing a worker for redundancy, the penalty for redundancy dismissals, along with indicators for whether employers must notify or gain approval from a third party to dismiss workers. Each variable is centered at zero across sample countries and scaled by their standard deviation, I then sum all variables to construct the index, which is then once again centered at zero and divided by its standard deviation. The signs of all variables are controlled such that higher values indicate more labor market frictions. Table I.1.1 summarizes the included variables before they are transformed.

Table I.1.1: Labor Market Frictions Index

	Mean	St. Dev	Minimum	Maximum
Days off Per week	1.04	0.36	0	2.0
Annual Leave	19.57	6.95	0	34.0
Days of Not. Dismissal for Red.	6.55	5.73	0	72.0
Severance	33.53	44.01	0	433.3
Not. Dismissal for Red.	0.51	0.48	0	1.0
Approval of Dismissal for Red.	0.18	0.39	0	1.0
Not. Collective Dismissal	0.63	0.50	0	1.0
Approval for Collective Dismissal	0.23	0.42	0	1.0
Penalty for Dismissal	0.16	2.50	0	43.3
Obs.	181	181	181	181

Note: Annual leave is days of paid annual leave, severance measures weeks of severance pay required when firing a worker for redundancy, Penalty for dis. measures the penalty for redundancy dismissal. Not. and App. of dis. are indicator variables for whether employers must notify or gain approval from a third party to dismiss workers respectively.

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In addition to estimating the effect of labor market frictions on trade with the index I also estimate the effect for each variable individually. In Table I.1.2 I report these results. All but the indicator variable for requiring notice before dismissing workers for redundancy takes on the same sign as the index. I also consider various different models, as I do with the index, estimating a Poisson, a Gamma and a Negative Binomial. The Poisson specification implies proportionality between the mean and variance while Gamma implies proportionality between the mean and standard deviation. Table I.1.2 reports my results for various estimators. It should be clear that the results from the previous table are not overly sensitive to these different model specifications. Once again, all but the indicator variable for requiring notice before dismissing workers for redundancy take on the same sign as the index. One slightly troublesome fact is the difference in the estimated effect of distance between the Poisson and the OLS and Gamma estimation. When OLS and Gamma estimation yields similar results and Poisson estimates are attenuated this is suggestive evidence of model misspecification.

Table I.1.2: Effect of Labor Market Frictions on Trade: Various Estimators

	(1) OLS	(2) Poisson	(3) Gamma	(4) Neg Bi
Log GDP	1.119***	0.778***	1.169***	1.170***
	(0.0230)	(0.0242)	(0.0249)	(0.0250)
Border	1.923***	1.754***	1.817***	1.817***
	(0.186)	(0.217)	(0.205)	(0.205)
Log Distance	-0.543***	-0.265**	-0.524***	-0.524***
	(0.0968)	(0.114)	(0.0885)	(0.0885)
Annual leave	-0.0569***	-0.0404***	-0.0298***	-0.0297***
	(0.00729)	(0.00413)	(0.00560)	(0.00561)
Approval of dismissal	-0.401***	-0.788***	-0.521***	-0.520***
	(0.101)	(0.0750)	(0.0801)	(0.0802)
Penalty for dismissal	-0.0115***	-0.0465***	-0.0281***	-0.0281***
	(0.00415)	(0.00596)	(0.00384)	(0.00384)
Severance	-0.00355**	0.00312***	-0.000589	-0.000583
	(0.00139)	(0.00113)	(0.00126)	(0.00126)
Not. dismissal	0.443***	0.630***	0.466***	0.465***
	(0.0979)	(0.0760)	(0.0801)	(0.0801)
Fixed Effects	ind, yr	ind, yr	ind, yr	ind, yr
Observations	119162	175787	175787	175787

Note: Dependent for OLS estimation is log total value of imports by year and source country, the dependent variable for Poisson, gamma and negative binomial estimation is the level of total imports as is common in the literature. All specifications include year and industry fixed effects. Standard errors are clustered at the source country level. Annual leave is days of paid annual leave, severance measures weeks of severance pay required when firing a worker for redundancy, Penalty for dis. measures the penalty for redundancy dismissal. Not. and App. of dis. are indicator variables for whether employers must notify or gain approval from a third party to dismiss workers respectively.
Standard errors in parentheses
+ $p < .20$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I.2 Industry Variables

The industry specific variables considered when estimating the effect of skill intensity on the related party trade share include: the production employment share, capital per workers, plant specific capital per worker, equipment capital per worker, industry specific demand elasticity, upstreamness, R&D, and contractablility. Employment and capital per worker data is take from the NBER-CES Manufacturing Industry Database. I use a time invariant average from 1995-2005 for all industries. The measure of demand elasticities are estimated by Broda and Weinstein (2006). R&D data is derived from the Orbis database, which includes information on over 30 million companies both private and public as well as domestic and international. The measure used is calculated as the natural log of global R&D expenditures divided by firm sales in each industry. This is the same data used in **?**. Both upstreamness, and contractablility are constructed by me for this paper, what follows is a detailed review of these industry controls.

I.2.1 Nunn Index

The Nunn (2007) measure of the contract intensity of goods or relationship-specificity of goods, which is based on the differentiation of intermediate inputs as in Rauch (1999). Two measures of contract intensity are constructed as:

$$z_i^1 = \sum_j \theta_{ij} R_j^{diff} \quad \text{and} \quad z_i^2 = \sum_j \theta_{ij} \left(R_j^{diff} + R_j^{refprice} \right). \tag{1}$$

Where θ_{ij} is the share of input from industry j used in industry i, R_j^{diff} is the proportion of input j that are differentiated, and $R_j^{refprice}$ is the proportion of input j that is not sold on an exchange but are reference priced. Both contract intensity measures classify the proportion of inputs that are relationship-specific, but the second measure is more broadly defined as it also includes reference-priced inputs as being relationship-specific.

I.2.2 Upstreamness

I utilize a measure of upstreamness proposed by Antràs et al. (2014), which intuitively measures a products positions in the economy-wide supply chain as its average distance from end use. This measure of an industry's position on the supply chain, U_i is greater than or equal to 1, with more upstream industries having larger values. While it might seem that calculating U_i requires an infinite sum Antràs et al. (2014) show that a column vector containing each industries measure of U_i (I will call this vector U) can be generated with the following formula:

$$U = [1 - \Delta]^{-1}\mathbf{1}$$

where Δ is an $N \times N$ matrix with elements $\hat{d}_{ij}$ and $\mathbf{1}$ is a column vector of ones. $\hat{d}_{ij}$ is an open economy adjustment of d_{ij} such that $\hat{d}_{ij} = d_{ij}\frac{Y_i}{Y_i - X_i + M_i}$, where M_i and X_i denote exports and imports of sector i's output.[1]

For my analysis I use BEA provided Input-Output (I-O) tables to construct the Δ matrix. The most disaggregate I-O table which is publicly available through the BEA's website is for 2002. This table includes a total of 446 industries measured as 6 digit NAICS codes. In my analysis I will restrict ourselves to manufacturing industries of which I have 272. I use the Supplementary Use Table, in which the (i, j)th element corresponds to the value of industry i's output used in production of industry j's output. To make the open economy adjustments I subtract net exports and net change in inventories from total industry output (Y_i). After making this adjustment I can construct Δ and calculate $U = [1 - \Delta]^{-1}\mathbf{1}$.

Over the 272 industries for which I compute U_i my measure ranges from 1.00 to 3.62.[2] My measure has a median value of 1.249 a mean of 1.494 and a standard deviation of 0.541. Once I have constructed my measure of upstreamness at the NAICS 6 level I then take a weighted average of estimates to construct a measure of upstreamness at the NAICS 4, which is the level of variation of my skill intensity

[1] Antràs et al. (2014) show that an additional assumption must be made that $X_{ij}/X_i = M_{ij}/M_i$. This assumption imposes that the share of a country's industry i output used in industry j (at home or abroad).

[2] The lowest being NAICS 333112: lawn and garden tractor and home lawn and garden equipment) and the highest being NAICS 325110: petrochemical manufacturing. Antràs et al. (2014) also computes petrochemical as the most upstream industry yet their index value is 4.651.

measure. I use the average of NAICS 6 imports and exports as weights allowing heavily traded NAICS six industries to have a larger effect the NAICS four average.

I.3 Skill intensity and the RP trade share

Occupation specific skill intensity (SI_j) is meant to capture critical thinking skills. Using BLS O*NET data to measure occupational characteristics has also be used by Jensen and Kletzer (2010) and Autor (2011). My critical thinking index is constructed using five skills including critical thinking, active learning, complex problem solving, judgment and decision making and troubleshooting. Table

Table I.3.1: A Measure of Occupation Skill Intensity

Occupation	**Index value**
Lowest Values	
Graders and sorters, agricultural products	7.623
Models	8.723
Maids and Housekeeping Cleaners	8.790
Locker Room, Coatroom, and Dressing Room Attendants	8.906
Funeral attendants	9.230
Telemarketers	9.239
Highest Values	
First-Line Supervisors/Managers of Farming, Fishing, and Forestry Workers	66.752
Engineering technicians, except drafters	69.326
Physicians and Surgeons, All Other	69.884
Producers and directors	78.380
Compliance Officers	95.247
Engineers	107.083

I.3.1 reports the highest and lowest six occupations by my critical thinking index. I then use each occupations' employment in industry i in year t (emp_{ijt}) gathered from the Occupational Employment Statistics (OES) to constructing an industry specific skill intensity measure (SI_{it}) as follows:

$$SI_{it} = \sum_j \frac{SI_j \times emp_{ijt}}{\sum_j emp_{ijt}} \tag{2}$$

The OES dataset allows me to construct industry specific critical thinking skill indexes for NAICS 4 manufacturing industries, yielding a panel of 83 industries over 10 years. Among the least skill intensive industries are leather and tobacco manufacturing and among the most skill intensive are aerospace pharmaceutical manufacturing.[3]

There is strong correlation between the skill intensity of an industry and the skill intensity of its intermediate inputs. Since many commodities are likely imported not only by their own industry but also the industries which use these commodities as intermediates I also constructed a measure of the skill intensity of industries' that purchase industry i's output as an intermediate. This allows me to assess the correlation between these downstream industries skill intensity and the RP import share of industry i. To construct a measure of downstream skill intensity, I will use BEA input output tables. Letting θ_{ikt} be the purchase from industry i by industry k, I will construct downstream skill intensity

[3] As noted by Voigtlander (2013) there is a strong correlation between the skill intensity of an industry and the skill intensity of its intermediate inputs. Since many commodities are likely imported not only by their own industry but also the industries which use these commodities as intermediates I also constructed a measure of the skill intensity of industries' that purchase industry i's output as an intermediate. This allows me to assess the correlation between these downstream industries skill intensity and the RP import share of industry i. To construct a measure of downstream skill intensity, I will use BEA input output tables. Letting θ_{ikt} be the purchase from industry i by industry k, I will construct downstream skill intensity as: $SI_{it}^{DS} = \sum_k \frac{SI_{kt} \times \theta_{ikt}}{\sum_k \theta_{ikt}}$. Result for all of the following tests using this downstream skill intensity can be found in the table I.5.1

as:

$$SI_{it}^{DS} = \sum_k \frac{SI_{kt} \times \theta_{ikt}}{\sum_k \theta_{ikt}}.$$

I.4 A Measure of Offshoring

My measure of industry specific offshoring, is adapted from Feenstra and Hanson (1996) and measures offshoring for an industry i in time t as:

$$Off_{it} = \frac{\sum_k \left[\theta_{ikt} \times \left(\frac{IMP_{kt}}{CONS_{kt}}\right)\right]}{\theta_{it}}. \tag{3}$$

Where θ_{ikt} is defined as intermediates purchased by industry i from industry k in time t and $\theta_{it} = \sum_k \theta_{ikt}$ or the sum of all intermediates purchased by industry i. IMP_{kt} are total U.S. imports of k's goods and $CONS_{kt}$ is domestic consumption of k, both in time t. This measure of offshoring assumes that each industry i imports a share of its purchases from industry k equal to the economy wide import share, which has been called the "comparability assumption." Put another way, this measure of offshoring assumes that the economy-wide import share of intermediate consumption in an industry k is the same as the import share of intermediates purchased by industry i. I restrict industries k and i to have the same 3 digit NAICS code in an attempt to focus on intermediates that industry i could feasibly produce themselves. To compute the purchases of inputs by industry i from industry k, I start with the 2002 BEA detailed use input-output table, which details the value of inputs purchased by each industry other industries. Domestic consumption of goods from industry k is computed annually from production data in the Annual Survey of Manufacturers to which I then subtract exports and add imports from census trade flows.

I collected U.S. Related party trade flows data from the U.S. Census Bureau which distinguishes U.S. imports by ownership structure (RP and NRP), year, and source country type at the NAICS 6 level of aggregation. The U.S. data are publicly available at: http://sasweb.ssd.census.gov/relatedparty/. This website permits downloading the data at the six-digit NAICS level. The six-digit Harmonized System data are available from the U.S. Census for a fee. Using this data I generate three different import share measures corresponding to three different measures of offshoring: the traditional "Feenstra Hanson" measure previously described, as well as two new measures that distinguish between related party and non-related party offshoring, $\text{RPoff}_{i,t}$ and NRPoff_{it}, constructed as follows,

$$RPoff_{it} = \frac{\sum_k \left[\theta_{ikt} \times \left(\frac{RP_{kt}}{CONS_{kt}}\right)\right]}{\theta_{it}}, \tag{4}$$

and

$$NRPoff_{it} = \frac{\sum_k \left[\theta_{ikt} \times \left(\frac{NRP_{kt}}{CONS_{kt}}\right)\right]}{\theta_{it}}. \tag{5}$$

$RPoff_{i,t}$, $NRPoff_{it}$ should sum to total offshoring (off_{it}) but because some trade flows are not reported as either RP or NRP, this is not always the case. However, these non-designated flows are a very small minority of total flows, less than 2 percent on average.Table I.4.1 summarizes average RP and NPR offshoring by the NAICS 4 manufacturing industry over the period 2002-2011. These measures impose a second "comparability assumption," that each industry i's purchases of imported intermediates from industry k mirrors the economy wide intra-firm import share of purchases in industry k

Table I.4.1: Average Offshoring and Skill Intensity by Industry, 2002-2011

	Offshoring			Critical Thinking	Employment Share
Industry	total	RP	NRP	Skill Intensity	in offshorable Occ.
3111	2.8%	1.0%	1.8%	12.47	86%
3112	41.9%	9.7%	32.2%	12.32	82%
3113	29.0%	17.6%	11.5%	11.68	84%
3115	5.4%	2.4%	3.0%	12.97	89%
3116	7.2%	1.6%	5.7%	11.44	92%
3118	9.5%	3.0%	6.4%	11.85	90%
3119	11.2%	3.0%	8.2%	12.31	86%
3121	28.9%	5.3%	23.3%	12.52	82%
3122	5.7%	2.2%	3.4%	10.43	71%
3132	37.7%	6.3%	31.4%	12.36	89%
3133	33.1%	10.8%	22.2%	11.45	82%
3141	14.5%	2.5%	12.0%	12.08	88%
3149	24.8%	14.1%	10.7%	11.53	84%
3211	17.0%	4.1%	12.9%	12.70	91%
3212	26.3%	7.4%	18.9%	12.83	88%
3219	19.3%	3.6%	15.6%	13.19	88%
3221	46.4%	19.4%	27.0%	13.33	85%
3222	20.7%	11.0%	9.7%	12.04	84%
3231	43.7%	7.3%	36.4%	8.24	58%
3241	15.7%	8.2%	7.5%	15.19	85%
3251	25.6%	12.4%	13.2%	15.10	87%
3252	17.5%	9.3%	8.2%	14.22	85%
3253	38.4%	18.6%	19.8%	13.52	84%
3254	47.8%	38.5%	9.3%	15.45	83%
3255	8.6%	4.1%	4.5%	13.11	84%
3256	11.8%	4.7%	7.0%	13.08	86%
3259	26.4%	19.9%	6.5%	12.88	81%
3261	12.4%	3.6%	8.8%	12.88	88%
3262	37.6%	18.7%	18.8%	13.77	88%
3271	68.7%	15.8%	52.9%	14.87	85%
3272	26.3%	9.7%	16.6%	13.14	86%
3273	9.3%	3.1%	6.3%	14.99	92%
3274	2.7%	0.7%	2.0%	13.32	81%
3279	31.7%	4.6%	27.1%	13.97	86%
3311	33.3%	14.4%	18.9%	13.34	84%
3312	27.2%	9.9%	17.4%	13.41	87%
3313	33.9%	19.0%	14.9%	13.02	87%
3314	78.3%	22.5%	55.9%	12.92	84%
3322	38.3%	11.5%	26.7%	12.92	85%
3323	12.2%	4.7%	7.5%	14.43	90%
3324	22.1%	7.0%	15.0%	14.64	88%
3329	36.4%	13.3%	23.1%	14.10	87%

Industry	total	Offshoring RP	NRP	Critical Thinking Skill Intensity	Employment Share in offshorable Occ.
3331	39.6%	22.4%	17.2%	14.66	87%
3332	53.5%	24.2%	29.3%	14.57	84%
3333	92.2%	48.4%	43.8%	13.80	80%
3334	23.0%	11.7%	11.2%	13.56	86%
3335	53.2%	26.7%	26.5%	14.09	90%
3336	44.5%	27.5%	17.0%	13.75	86%
3339	35.2%	17.0%	18.1%	14.54	87%
3341	71.6%	45.8%	25.8%	12.89	65%
3342	53.0%	32.5%	20.5%	13.96	76%
3344	46.7%	26.7%	20.0%	14.84	84%
3345	41.0%	27.2%	13.8%	15.69	81%
3346	65.1%	37.7%	27.4%	9.50	61%
3351	56.4%	31.4%	25.0%	12.22	81%
3352	57.9%	19.9%	38.0%	11.62	78%
3353	42.1%	24.5%	17.6%	13.79	88%
3359	42.5%	19.3%	23.2%	12.95	84%
3361	69.5%	65.8%	3.7%	8.28	53%
3362	9.3%	5.0%	4.3%	14.00	87%
3364	33.6%	11.2%	22.3%	17.28	85%
3366	12.8%	4.9%	7.8%	15.06	85%
3369	50.5%	29.6%	20.9%	13.22	81%
3371	67.1%	7.8%	59.2%	13.47	91%
3372	32.1%	7.3%	24.8%	13.20	86%
3379	24.5%	5.3%	19.0%	11.27	80%
3391	32.3%	18.0%	14.3%	13.12	82%
3399	40.3%	10.5%	29.8%	12.93	80%
		Unweighted Average			
		Offshoring		Critical Thinking	Employment Share
	total	RP	NRP	Skill Intensity	in offshorable Occ.
	33.4%	14.9%	18.5%	13.17	83.6%
		Correlation Matrix			
total	1				
RP	0.7963	1			
NRP	0.7851	0.2504	1		
skill int.	-0.0448	-0.0726	0.0027	1	
Emp. Shr.	-0.4318	-0.5636	-0.1137	0.5916	1

Note: For each industry total, RP and NRP are constructed with the Feenstra Hanson method described in the paper and then averaged over 2002 through 2011. The critical thinking index and employment share of offshorable occupations are constructed using the 85% offshorability threshold, which is the main threshold used in estimation.

I.5 Regression results for Downstream Skill Intensity

I repeat the same specification as the main text in Table I.5.1 with downstream skill intensity as the depended variable.

$$RP_{ijt}/(RP_{ijt} + NRP_{ijt}) = \alpha + \beta_1 SI_{it}^{DS} + \gamma Z_i + \rho_t + \rho_j + \epsilon_{ij,t}, \quad (6)$$

In the fully saturated model a one standard deviation increase in critical thinking skill intensity leads to a 0.05 standard deviation increase in the RP trade share, or an increase in RP trade share of 5.9 percent. I take these results as suggestive evidence that both industry specific critical thinking and downstream critical thinking intensity create an incentive for firms to vertically integrate.

Table I.5.1: Downstream Critical Thinking Intensity and RP Trade

	Dependent variable: Industry Related Party Import Share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Upstream Critical Thinking	0.151***	0.102***	0.116***	0.0817**	0.0671**	0.0329	0.0794**	0.0500*
	(0.0178)	(0.0197)	(0.0216)	(0.0344)	(0.0331)	(0.0304)	(0.0328)	(0.0296)
Prod emp share		-0.448***	-0.486***	-0.445***	-0.527***	-0.308***	-0.412***	-0.253**
		(0.0724)	(0.0743)	(0.0700)	(0.0757)	(0.102)	(0.0813)	(0.104)
Nunn Index			0.452***	0.476***	0.360**	0.392***	0.332**	0.399***
			(0.136)	(0.144)	(0.162)	(0.135)	(0.130)	(0.120)
Capital per worker				0.0314				
				(0.0285)				
Plant per worker					-0.115*	-0.141**	0.0312	-0.0175
					(0.0592)	(0.0578)	(0.0644)	(0.0640)
Equipt per worker					0.112**	0.132***	0.0474	0.0760*
					(0.0436)	(0.0411)	(0.0450)	(0.0427)
R&D						7.030***		5.999***
						(1.726)		(1.715)
upstream							0.00645***	0.00610***
							(0.00156)	(0.00149)
(high sigma)*upstream							0.000936	-0.0000277
							(0.00197)	(0.00199)
high sigma							-0.0529	0.0307
							(0.116)	(0.121)
Year Fixed Effects	X	X	X	X	X	X	X	X
Country Fixed Effects	X	X	X	X	X	X	X	X
R^2	0.131	0.137	0.139	0.139	0.140	0.144	0.146	0.150
Observations	264302	264302	264302	264302	264302	264302	264302	264302

Note: Table I.5.1 reports the effect of downstream critical thinking skill intensity on the RP trade share for 83 four digit NAICS industries. The dependent variable is the RP trade share for industry i at time t, SI_{it} controlling for skill intensity as well as time fixed effects. Industry controls include the share of production works in an industry and the contractability of industry inputs as defined by Nunn (2007). I also control for industry estimates of value added, capital expenditures and capital per worker from the NBER productivity database as Antras and Yeaple(2013) have shown these are correlated with the RP trade shares. I also control for industry level R&D levels, the data for which originated from the Orbis database and were provided by Nathan Nunn and Danial Trefler. I employ a measure which is calculated as the natural log of global R&D expenditures divided by firm sales in each industry. Lastly, I control for the demand elasticities as estimated by Broda Weinstein (2006) along with an industry specific measure of position on the global value chain, which has shown can influence firms incentive for ownership. Standard errors are clustered at the industry level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I.6 A Measure of Offshorability

For more than 800 occupation the O*NET database provides measure of both the "importance" and "level" required for a set of skills and tasks. Constructing the geometric mean of these two scores $Imp^{1/2} * Lvl^{1/2}$, then summing across attributes I constructs a index of offshorability of a occupation where higher values correspond to less offshorable occupations. The standard deviation of my index is

.623. One standard deviation decrease in offshorability is takes you from the occupation of "Textile Knitting and Weaving Machine Setters" to "Tile and marble setters" while an additional standard deviation decrease in offshorability take you to "Operators, and Tenders and a Medical and clinical laboratory technicians" Allowing the cutoff level of offshorability to vary has little effect on my results. Results are not especially sensitive to the chosen cutoff, where I compare results with 65, 75 85 and 90 percent of occupations designated as offshorable.

I.7 Instrumenting for Offshoring Cost

I.7.1 Validity of Exclusion Restriction

My instrument set is not directly analogous to the Feenstra Hanson measure since I do not control for domestic consumption, rather than thinking of this as a measure of industry i offshoring intensity, think of it as a measure of the cost of offshoring which is driven purely by the change in exports of the input of industry i. Using these instrument sets separately will result in a just identified model while using them in concert will allow me to estimate an over identified model and test for the validity of each instrument. My identification strategy relies on the exclusion restriction that my instrument set is uncorrelated with U.S. demand shocks as well as U.S. productivity shocks. Both are likely be correlated with both wages and levels of U.S. offshoring. In an effort to show that the exclusion restriction holds I provide evidence that my instruments are uncorrelated with U.S. productivity. To do so, I regressed my RP and NRP offshoring measures on the full instrument set. I then take predicted U.S. offshoring and regress it on three measures of US productivity. If my instrument set is truly orthogonal to U.S. productivity shocks, this measure of predicted offshoring should be uncorrelated with U.S. productivity. Table I.7.1 reports the results from this exercise.

Table I.7.1: Orthogonality of Instrument Set

	(1) RP	(2) NRP	(3) RP	(4) NRP	(5) RP	(6) NRP
labor productivity	-0.000555 (0.000953)	0.000352 (0.00147)				
multi-factor productivity			-0.00283 (0.00170)	-0.000214 (0.00180)		
capital productivity					-0.00326** (0.00132)	-0.00139 (0.00122)
Fixed Effects	ind, yr, occ	ind, yr, occ	ind, yr, occ	ind, yr, occ	ind, yr, occ	ind, yr, occ
Observations	602	607	602	607	602	607
Adjusted R^2	0.891	0.957	0.891	0.957	0.891	0.957

Note: For each industry total, RP and NRP are constructed with the Feenstra Hanson method described in the paper and then regressed on the instrument set Chinese RP and NRP export to the rest of the world along with Chinese NRP exports to Developed Countries. I then take predicted US offshoring and regress it on three measures of US productivity. All three measure are constructed by the Bureau of Labor Statistics at the NAICS 4 level. Standard errors in parentheses and clustered at the NAICS4 industry level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Throughout the sample period U.S. imports from China are roughly the same as developed economy imports from China for both RP and NPR trade. Additionally developed country RP and NRP imports from China follow a similar time series as U.S. imports for both RP and NRP flows, exhibiting a steep increase in both RP and NRP imports from China after WTO accession in 2001, drastically reducing trade costs.

I.7.2 Bias under Ordinary Least Squares

As discussed in the main text, under the assumption that wages are a function of offshoring costs and the level of demand, OLS is expected to generate a bias which will attenuate results for both RP and

NRP offshoring. In this section I present full OLS results as well as a more detailed description of this bias. I will consider a simplified case where offshoring, both RP and NPR effect wages but there are not differential effects based on occupation or industry characteristics. Let the level of offshoring be a function of both offshoring costs and industry demand.

$$RP_i = \beta_0 + \beta_1 D_i^{RP} + \beta_2 RP_i^c + \epsilon_i \tag{7}$$

$$NRP_i = \pi_0 + \pi_1 D_i^{NRP} + \pi_2 NRP_i^c + \epsilon_i \tag{8}$$

Where RP^c/NRP^c represent the cost of offshoring and D^{RP}/D^{NRP} are industry demand shocks, which may or may not differentially effect RP and NRP offshoring. Allowing wages to be a function of both demand shocks and the cost of offshoring as follows,

$$w_i = \alpha_0 + \rho_1 RP_i^c + \rho_2 NRP_i^c + \gamma_1 D_i^{RP} + \gamma_2 D_i^{NRP} + \epsilon_i \tag{9}$$

it is clear that using realized offshoring as a measure of offshoring costs will be correlated with the unobserved demand shocks and therefore will bias results. By solving (7) and (8) for offshoring cost and plugging them into the wage equations I can see that the sign of the bias depends on the signs of ρ_1 and ρ_2.

$$w_i = \hat{\alpha}_0 + \frac{\rho_1}{\beta_2} RP_i + \frac{\rho_2}{\pi_2} NRP_i + \left(\gamma_1 - \frac{\rho_1 \beta_1}{\beta_2}\right) D_i^{RP} + \left(\gamma_2 - \frac{\rho_2 \pi_1}{\pi_2}\right) D_i^{NRP} + \epsilon_i \tag{10}$$

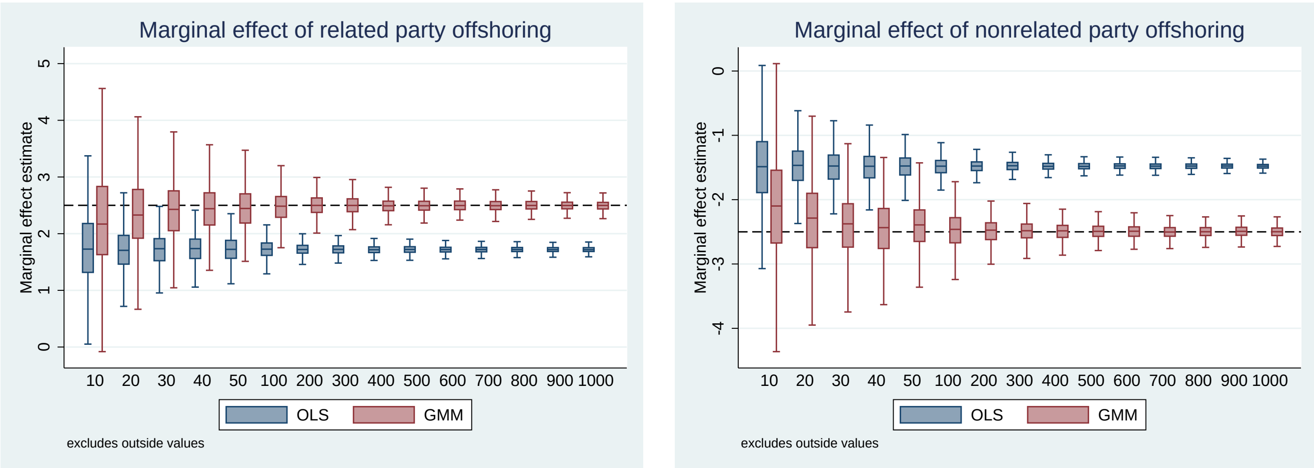
Under the assumption that $\rho_1 > 0$ and $\rho_2 < 0$ along with γ_1, γ_2, β_2 and π_2 all being greater than zero, the estimate of both reduced form coefficients will be attenuated.

I.7.3 Simulated Bias

To demonstrate this bias more clearly, I simulated the system I described in equations (7), (8) and (9). I implement the following parameterization for the equations (7) and (8): $\beta_0 = 1$, $\beta_1 = 3$, $\beta_2 = 2$, $\pi_0 = 1$, $\pi_1 = 3$, $\pi_2 = 2$. For the wage equation I set $\alpha = 1$, $\rho_1 = 5$, $\rho_2 = -5$ and lastly I set $\gamma_1 = \gamma_2 = 1$. For all four equations include normally distributed and independent error. From equation (10) under this parameterization, an unbiased estimate of the reduced from effect of RP and NRP offshoring on wages is 2.5 and -2.5 for RP and NRP respectively. However, due to the correlation between observed offshoring and demand shocks, if demand shocks are unobserved, OLS will results in estimates which are attenuated and therefore biased.

To demonstrate the sign of the bias I run 1,000 simulations on datasets ranging in size from 10 to 1,000 observations. I estimated the marginal effect of offshoring costs on wages using both OLS and a GMM with an instrument set for offshoring costs which in constructed using true offshoring costs plus random error. In figure I.7.1 I plot the distribution of estimates across different sized datasets. As you can see, GMM does a good job of removing bias and as would be expected OLS remains biased and in both cases attenuates results. Comparing the estimates on the U.S. data using OLS to the GMM results reported in the paper one can see the same phenomena of attenuated results. I report both GMM and OLS results in Table I.7.2. The main effects of RP and NRP offshoring demonstrate a bias which is consistent with what we expect to observe. Additionally, these GMM results are qualitatively constant with our main 2SLS results and we fail to reject the null hypothesis that our model is overidentified at the 5% level of significants.

Figure I.7.1: Simulated bias estimates



Note: The above graphs are constructed by simulating the system described in appendix I.7.2 1,000 times and then estimating reduced form estimates of the effect of RP and NRP offshoring using 10 through 1,000 observations. The True marginal effect is 2.5 for RP offshoring and -2.5 for NRP offshoring, and is labeled with a dotted line in both panels. The box and whisker plots displays the median, 25th and 75th percentiles with the box and the 95th and 5th percentiles with the whiskers.

Table I.7.2: Effect of Related and Non-Related Party Offshoring on Average Wages

	GMM				OLS
	(1)	(2)	(3)	(4)	(5)
RP	0.0678	0.557***	0.354***	0.325***	0.0886***
	(0.0789)	(0.114)	(0.0769)	(0.0719)	(0.0254)
NRP	0.155**	0.358***	-0.191***	-0.257***	0.0149
	(0.0700)	(0.137)	(0.0712)	(0.0724)	(0.0228)
RP*offble		-0.173***	-0.182***	-0.126***	-0.0850***
		(0.0472)	(0.0464)	(0.0312)	(0.0264)
NRP*offble		0.00970	0.00800	0.0374	-0.00351
		(0.0311)	(0.0291)	(0.0296)	(0.0218)
RP*HS			0.0245	0.103**	0.0275
			(0.0174)	(0.0469)	(0.0175)
NRP*HS			0.342***	0.265**	-0.0397**
			(0.103)	(0.114)	(0.0184)
RP*offble*HS				-0.0782*	-0.0277
				(0.0445)	(0.0182)
NRP*offble*HS				0.0808	0.0436**
				(0.0527)	(0.0189)
Year Fixed Effects	X	X	X	X	X
Industry Fixed Effects	X	X	X	X	X
Occupation Fixed Effects	X	X	X	X	X
Hanson's J P-value	0.000	0.376	0.107	0.087	NA
R^2	0.336	0.299	0.288	0.287	0.355
Observations	49792	49792	49792	49792	49792

Note: The dependent variable is an occupation by industry estimate of the average wage from the OES, measured at the NAICS 4. RP and NRP are the measures of industry offshoring, offble is an indicator variable equal to one for offshorable occupations and HS is an indicator variable equal to one for high skill industries. In the GMM estimation, supply driven change in offshoring are instrumented for using RP and NRP export from China to Europe as well as NRP exports to the world minus the U.S. The sample is restricted to 2002-2007 in an effort to avoid the period of highly correlated demand shocks between the U.S. and Europe. For all IV specifications I can reject the null hypothesis that offshoring is exogenous at the 5% level. All specifications include industry specific linear time trends along with industry, year and occupation fixed effects. Standard errors are clustered at the occupation level and reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

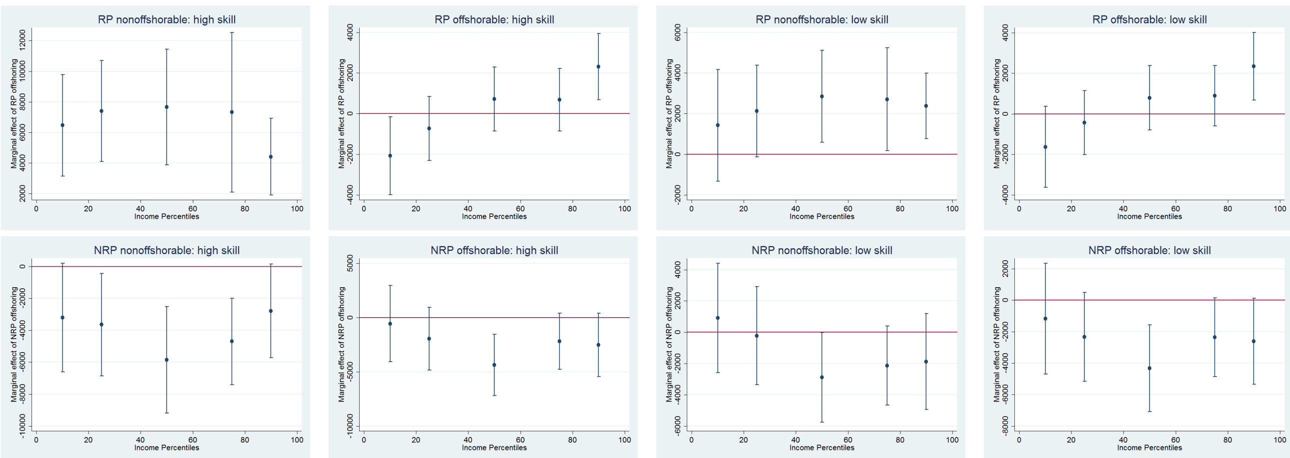
I.8 The Effect of Offshoring on Income Inequality, OES

As is discussed in the main text, the theoretical model implies that changes in offshoring costs will impact the industry specific wage distribution.The main text uses the ACS to test these predictions, however we can attempt to test these predictions with the OES as well.

From the OES, I utilizing wage data detailing the 10th, 25th, 50th, 75th and 90th percentiles of the wage distribution for each occupation industry pair. Recently Oldenski (2012) employed this OES data to investigate the effect of offshoring on polarization of wages however, this work does not address NRP offshoring because it uses foreign employment by multinationals as the basis of her measure of offshoring. My measure of offshoring is different than Oldenski (2012) but, by estimating equation our main estimating equation on different percentiles of the occupation-industry wage distribution, the estimation strategy is similar.

Figure I.8.1 plots the total effects of RP and NRP offshoring for offshorable and non-offshorable occupations employed in high and low skill industries. RP offshoring appears to have a positive effect on wages for non-offshorable occupations across the wage distribution, while for offshorable occupations RP offshoring decreases wages at the bottom of the distribution while increasing them at the top, suggesting that RP offshoring increases residual inequality among offshorable occupations. The effect of NPR offshoring appears to be generally negative with the strongest effect on median wages. These results generally support my average wages findings, while adding additional nuance to the effect of RP offshoring on offshorable occupations. For both high and low skill industries I found essentially no effect of RP offshoring driven by a fall in offshoring costs. It is now apparent that there is an effect, however it is simply heterogeneous across the income distribution, while the wage of high earners rise the wages of low earners fall.

Figure I.8.1: The effect offshoring across wage distribution



Note: The above figures plot the coefficients from Table **??** along with 95% confidence intervals from tests joint of significance. All specifications are estimated with occupation, industry and time fixed effects and a full complement of interactions for offshorability and skill intensity. The dependent variables include the 10th, 25th, 50th, 75th and 90th percentiles of the occupation-industry specific wage distribution. Standard errors are clustered at the level of the occupation.

There are limitations to the OES that make it difficult to evaluate the models predictions regarding the effect of offshoring on the distribution of wages. First the OES is top coded which limits my ability to observe wage variation at the high end of the distribution. Second observing wages at only these specific percentiles gives limited information about the effect of offshoring on the overall distribution. As a result of these limitations I employ wage and employment data from the ACS in the main text, which I believe to give a better measure of the effect of offshoring on inequality.[4]

[4]The ACS provided industry codes which are based on but not directly comparable to NAICS industry classifications. As a result I are limited to a subset 50 industries which are comparable to the four digit NAICS industries considered in the precious section.

Part II
Theoretical Appendix

II.1 Firm Problem, Matching and Screening, Revenue and Wages

II.1.1 Revenue Function

Given my assumptions regarding production, the share of income devoted to each sector Z and X will be as follows:

$$E = ZP_Z + XP_X$$

$$E_Z = \eta E, \quad E_X = (1-\eta)E$$

Given the level of expenditures in the Z sector, E_Z I can express the revenue of each firm in this sector as follows:

$$r(\theta) = p(\theta)q(\theta),$$

where

$$p(\theta) = E_Z^{\frac{1}{\sigma}} \widetilde{P}^{\frac{\sigma-1}{\sigma}} z(\theta)^{\frac{-1}{\sigma}},$$

and $\widetilde{P}$ is the well known price index for CES preferences, given by

$$\widetilde{P} = \left[\int_{\theta\in\Theta} p(\theta)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}.$$

Combining the above three equations I can express revenue in terms of $z(\theta)$, total expenditures E and the price index $\widetilde{P}$

$$r(\theta) = (\eta E)^{\frac{1}{\sigma}} \widetilde{P}^{\frac{\sigma-1}{\sigma}} z(\theta)^{\frac{\sigma-1}{\sigma}}.$$

II.1.2 Production and Revenue under Vertical Integration

Beginning with the production function in the Z sector,

$$z(\theta) = \theta H^{\gamma} G^{1-\gamma}$$

where,

$$H = \bar{\alpha}_h n_h(\theta)^{\beta_h} \qquad G = \bar{\alpha}_g^{\lambda} n_g(\theta)^{\beta_g}.$$

Note that if a firms opens v_i vacancies and therefore matches with m_i workers and does not hire any worker with ability less than $\alpha_{c,i}$ then they will fill a measure of vacancies n_i given by

$$n_i = m_i \left(\frac{\alpha_{min}}{\alpha_{c,i}} \right)^k.$$

An attractive feature of a Pareto distribution is the fact that a truncated Pareto remains Pareto so by choosing a cutoff skill level α_c, i allows you to control the average skill level as:

$$\bar{\alpha}_i = \frac{k\alpha_{c,i}}{(k-1)}$$

The production function for H and G in terms of the above equations is,

$$H = \frac{k\alpha_{c,h}}{(k-1)} \left[m_h \left(\frac{\alpha_{min}}{\alpha_{c,h}} \right)^k \right]^{\beta_h} \qquad G = \frac{k\alpha_{c,g}}{(k-1)}^{\lambda} \left[m_g \left(\frac{\alpha_{min}}{\alpha_{c,g}} \right)^k \right]^{\beta_g}$$

Given the production function for $z(\theta)$ I have the following:

$$z(\theta) = \theta\kappa_v m_g^{\beta_g(1-\gamma)} m_h^{\beta_h\gamma}(\alpha_{c,g})^{(\lambda-\beta_g k)(1-\gamma)}(\alpha_{c,h})^{(1-\beta_h k)\gamma},$$

where κ_v is defined as,

$$\kappa_v \equiv (\alpha_{min})^{\beta_h k\gamma+\beta_g k(1-\gamma)}\left(\frac{k}{k-1}\right)^{\gamma+\lambda(1-\gamma)}$$

The profit maximizing problem of the firm can then be expressed by the following:[5]

$$\begin{aligned}\Pi_V(\theta) \quad &= \max\left[\left(\tfrac{1}{1+\phi_h+\phi_g}\right)A_Z\left(\theta\kappa_v m_g^{\beta_g(1-\gamma)} m_h^{\beta_h\gamma}{\alpha_{c,g}}^{(\lambda-\beta_g k)(1-\gamma)}{\alpha_{c,h}}^{(1-\beta_h k)\gamma}\right)^{\frac{\sigma-1}{\sigma}}\right] \\ &\qquad -\left(f_V + C{\alpha_{c,g}}^{\delta}/\delta + C{\alpha_{c,h}}^{\delta}/\delta + b_h m_h + b_g m_g\right),\end{aligned}$$

where the firms choice variables are matching and screening for both headquarters and production employees: $\alpha_{c,h}$, $\alpha_{c,h}$, m_h and m_g. Fixed costs are meant to embody the cost associated with building facilities for production. Under outsourced production, fixed costs will also embody significant relationship-specific investments to find an arms-length supplier.

The first order conditions governing the firm's employment level are given by,

$$\frac{(\sigma-1)\gamma\beta_h}{\sigma(1+\phi_h+\phi_g)}r(\theta) = b_h m_h(\theta), \qquad \frac{(\sigma-1)(1-\gamma)\beta_g}{\sigma(1+\phi_h+\phi_g)}r(\theta) = b_g m_g(\theta). \tag{11}$$

Note that the optimal number of matches in the H sector are increasing in γ, which is the cost share of H in the production of $z(\theta)$. The optimal number of matches is also decreasing in the cost of filling vacancies in each labor market, b_h, and b_g. This should not be surprising but it makes clear the incentive for firms to offshore production if these costs are lower abroad.

The first order conditions governing the optimal screening thresholds are given by,

$$\frac{(\sigma-1)(1-\beta_h k)(\gamma)}{(1+\phi_h+\phi_g)\sigma}r(\theta) = C\alpha_{c,h}(\theta)^{\delta}, \qquad \frac{(\sigma-1)(\lambda-\beta_g k)(1-\gamma)}{(1+\phi_h+\phi_g)\sigma}r(\theta) = C\alpha_{c,g}(\theta)^{\delta}. \tag{12}$$

If revenue is increasing in θ, the productivity of the firm, the incentive to screen a firms workforce is also increasing in θ. So long as $\lambda/k > \beta_g$ there are returns to screening the workforce employed in the production of G, and wages will vary across firms depending on their optimal level of screening. This condition simply places a lower bound on the importance of skill in the production of G, given by λ, and a lower bound on the dispersion of skill within the economy, which is inversely proportional to k. In other words, in order for screening to play a role in this economy, worker skill must be sufficiently important and heterogeneous.

Utilizing the first order conditions from equation (11) and (12) along with the revenue function I can solve explicitly for screening, matching, and revenue as functions of the underlying parameters, where revenue is given by the following:

$$r_V(\theta) = (K_V)^{\frac{1}{\Gamma_1}\frac{\sigma-1}{\sigma}} A_Z^{\frac{1}{\Gamma_1}}\left[\theta b_h^{-\beta_h\gamma} b_g^{-\beta_g(1-\gamma)} C^{\frac{-(1-\beta_h k)\gamma-(\lambda-\beta_g k)(1-\gamma)}{\delta}}\right]^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}}, \tag{13}$$

[5]The standard CES revenue function is given by $r(\theta) = A_Z z(\theta)^{\frac{\sigma-1}{\sigma}}$, where A_Z is a demand shifter depending on total demand and the industry price in sector z and is given by $(\eta E)^{\frac{1}{\sigma}} P_Z^{\frac{\sigma-1}{\sigma}}$.

where K_V and Γ_1 are combination of parameters given by,

$$\begin{aligned} K_V &\equiv (\alpha_{min})^{\beta_h k\gamma+\beta_g k(1-\gamma)} \beta_g^{\beta_g(1-\gamma)} \beta_h^{\beta_h \gamma} \left(\frac{k}{k-1}\right)^{\gamma+\lambda(1-\gamma)} \\ &\times ((1-\beta_h k)\gamma)^{(1-\beta_h k)\frac{\gamma}{\delta}} \left[(\lambda-\beta_g k)(1-\gamma)\right]^{(\lambda-\beta_g k)\frac{(1-\gamma)}{\delta}} \\ &\times \left[\left(\frac{\sigma-1}{\sigma}\right)\frac{1}{(1+\phi_h+\phi_g)}\right]^{\Gamma_1-1}, \\ \Gamma_1 &\equiv 1-\left(\frac{\sigma-1}{\sigma}\right)\left[\frac{(\lambda-\beta_g k)(1-\gamma)}{\delta}+\frac{(1-\beta_h k)\gamma}{\delta}+\gamma\beta_h+(1-\gamma)\beta_g\right]. \end{aligned}$$

II.1.3 Wage Determination

As stated in the paper, under the mechanism put forth by **??** the solution to the worker firms bargaining problem is given by following expression:

$$\frac{\partial\left[r(n_h,n_g)-w_h(n_h,n_g)n_h-w_g(n_h,n_g)n_g\right]}{\partial n_i}=w_i, \quad i=h,p. \tag{14}$$

$$r(n_h,n_g)=(\eta E)^{\frac{1}{\sigma}}\widetilde{P}^{\frac{\sigma-1}{\sigma}}z(n_h,n_g)^{\frac{\sigma-1}{\sigma}}$$

along with the production function for $z(n_h,n_g)$

$$z(n_h,n_g)=\theta\left(\bar{\alpha}_h n_h^{\beta_h}\right)^{\gamma}\left(\bar{\alpha}_g n_g^{\beta_g}\right)^{1-\gamma}$$

I can describe wages as a functions of the derivative of the revenue function and their own derivative with respect to employment. Where the derivative the revenue function is given by

$$\frac{\partial r(n_h,n_g)}{\partial n_i}=\frac{\sigma-1}{\sigma}(\eta E)^{\frac{1}{\sigma}}\widetilde{P}^{\frac{\sigma-1}{\sigma}}\left(z(n_h,n_g)\right)^{-\frac{1}{\sigma}}\frac{\partial z(n_h,n_g)}{\partial n_i}$$

where,

$$\begin{aligned} \frac{\partial z(n_h,n_g)}{\partial n_h} &= \theta\left(\beta_h\gamma\right)^{1-\gamma}\left(\frac{\bar{\alpha}_g n_g}{\bar{\alpha}_h n_h}\right)^{1-\gamma} \\ \frac{\partial z(n_h,n_g)}{\partial n_g} &= \theta\left(\beta_g(1-\gamma)\right)^{\gamma}\left(\frac{\bar{\alpha}_h n_h}{\bar{\alpha}_g n_g}\right)^{\gamma} \end{aligned}$$

Note that under the assumptions on the screening technology I can ignore the derivative of average productivity with respect to employment, $\frac{\partial\bar{\alpha}_i}{\partial n_i}$ because the expected value of any workers productivity is equal to the average, therefore this term is equal to zero.

Given all of the above, the system of differential equations can be expressed in terms of the revenue function, by multiplying and dividing the first term on the right hand side by n_g/n_g and n_h/n_h in the first and second equation respectively. Then wages are given by the following

$$w_h=\left(\frac{\phi_h}{1+\phi_h+\phi_g}\right)\frac{r(n_h,n_g)}{n_h}, \qquad w_g=\left(\frac{\phi_g}{1+\phi_h+\phi_g}\right)\frac{r(n_h,n_g)}{n_g},$$

$$\phi_h\equiv\beta_h\gamma\frac{\sigma-1}{\sigma}, \qquad \phi_g\equiv\beta_g(1-\gamma)\frac{\sigma-1}{\sigma}$$

and the firms share of revenue is simply the remainder, $\frac{r(n_h,n_g)}{1+\phi_h+\phi_g}$.

The solution to this system differential equations yields the intuitive result that the income share for labor employed in the two sectors represents their share of the revenue function. Writing the revenue function as

$$r(n_h,n_g)=Bn_h^{\phi_h}n_g^{\phi_g}$$

$$B \equiv (\eta E)^{\frac{1}{\sigma}} \widetilde{P}^{\frac{\sigma-1}{\sigma}} \left[\sigma \left(\alpha_h\right)^{\gamma} \left(\alpha_g\right)^{1-\gamma}\right]^{\frac{\sigma-1}{\sigma}}, \qquad \phi_h \equiv \gamma\beta_h \frac{\sigma-1}{\sigma}, \qquad \phi_g \equiv \beta_g(1-\gamma)\frac{\sigma-1}{\sigma}$$

The same proceeder applies to bargaining under outsourced production, for more information I refer the reader to the main text.

II.2 Outsourcing

We now go through the intermediate good producers problem in more detail under domestic outsourcing. The final good producer chooses $\alpha_{c,h}$, m_h and G to produce $z(\theta)$. Under the models assumptions on timing, firm also decides on a level g before bargaining over wages, therefore the profit function of the firm can be written as:

$$\begin{aligned} \Pi_O(\theta) \quad &= \max \left[\left(\tfrac{1}{1+\phi_h}\right) A_Z \left(\theta \kappa_o m_h^{\beta_h \gamma} {\alpha_{c,h}}^{(1-\beta_h k)\gamma} G^{1-\gamma}\right)^{\frac{\sigma-1}{\sigma}} \right] \\ &\qquad - \left(f_O + C{\alpha_{c,h}}^{\delta}/\delta + b_h m_h + P * P_g\right), \end{aligned}$$

where κ_o is a combination of parameters given by, $\kappa_o \equiv (\alpha_{min})^{\beta_h k \gamma} \left(\frac{k}{k-1}\right)^{\gamma}$. Maximizing with respect to the firm's choice variables, yields the following first order conditions:

$$\frac{(\sigma-1)\beta_h \gamma}{\sigma(1+\phi_h)} r(\theta) = b_h m_h(\theta) \tag{15}$$

$$\frac{(\sigma-1)(1-\beta_h k)\gamma}{\sigma(1+\phi_h)} r(\theta) = C\alpha_{c,h}(\theta)^{\delta} \tag{16}$$

$$\frac{(\sigma-1)(1-\gamma)}{\sigma(1+\phi_h)} r(\theta) = P * P_g. \tag{17}$$

Equation (17) is the only first order condition which is substantially different from that of the vertically integrated firm, because it relates the revenue of a final good producing firm, $r(\theta)$ to the revenue of the intermediate good producer, $P * P_g = r_g$, providing a one-to-one mapping between the revenue of both firms. The intermediate good producer receives a constant share of the final good producing firms revenue, however since that revenue is decreasing in the price of the intermediate, the intermediate good producer will maximize profits by maximizing the final good producer's revenue, conditional on its own costs.

Intermediate good suppliers search for labor by the same method as final goods producers, and therefore pay the same cost for filling vacancies (b_g) and have access to the same screening technology as final goods producers. Once matching and screening take place, firms and workers bargain to determine wages, where wages for workers employed by intermediate goods firms represent the value marginal profit of the labor:[6]

$$w_g = \frac{\phi_g}{1+\phi_g} \frac{r_g(n_g)}{n_g}, \tag{18}$$

Employing the first order conditions of the final good producer along with the derivation of wages paid to production employees in equation (18) I can express the profit maximizing problem faced by the intermediate producer in terms of its own choice variables, $\alpha_{c,g}$ and m_g as well as the final good producer's revenue $r(\theta)$ which is a function of P_g:

$$\Pi_g = \max \left\{ \left(\frac{1}{1+\phi_g}\right) \frac{(\sigma-1)(1-\gamma)}{\sigma(1+\phi_h)} r(\theta) - \left(C^{\delta}_{\alpha_{c,g}}/\delta + b_g m_g\right) \right\}$$

[6] Recall that $\phi_h \equiv \beta_h \gamma \frac{\sigma-1}{\sigma}$ and that $\phi_g \equiv \beta_g(1-\gamma)\frac{\sigma-1}{\sigma}$.

II.3 Explicit Productivity Cutoffs

In this appendix I will solve for the explicit productivity cutoffs in terms of underlying parameters. These cutoffs will be solved for the non-skill intensive and skill intensive cases. I will begin with the non-skill intensive case, wherein offshorers are more productive than all domestic sourcing firms.

II.3.1 Non-skill intensive industries

Industries which I call non-skill intensive are those for which domestic producers are less productive than offshorers regardless of ownership structure. Therefore, the four relevant cutoff productivities are ranks as follows: $\theta_O < \theta_V < \theta_O^* < \theta_V^*$. I will begin by deriving the expression for θ_O. Firms with productivity such that they are indifferent between production as a domestic outsourcer and exit has profits equal to zero, therefor the following holds,

$$\frac{\Gamma_2}{(1+\phi_h)} r_O(\theta_V) - f_O = 0$$

Utilizing equation (**??**) as an expression for revenue I can also solve explicitly for the θ_O as follows,

$$\theta_O = \left\{ \frac{\Gamma_2 (K_O)^{\frac{1}{\Gamma_1}} (A_Z)^{\frac{1}{\Gamma_1}}}{f_O(1+\phi_h)} \left[b^{-(\beta_g(1-\gamma)+\beta_h\gamma)} C^{[-(1-\beta_h k)\gamma-(\lambda-\beta_g k)(1-\gamma)/\delta]} \right]^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \right\}^{\frac{\sigma}{1-\sigma}\Gamma_1} \tag{19}$$

By the same logic, the profits for firms with productivity θ_V is such that the profitability of domestic vertical integration is the same as domestic outsourcing, so the following must hold,

$$\frac{\Gamma_1}{(1+\phi_h+\phi_g)} r_V(\theta_V) - f_V = \frac{\Gamma_2}{(1+\phi_h)} r_O(\theta_V) - f_O.$$

Substituting equations (13) and (**??**) for $r_V(\theta_V)$ and $r_O(\theta_V)$ I solve for θ_V as,

$$\theta_V = \left\{ (f_V - f_O) \left[\left(b^{-(\beta_g(1-\gamma)+\beta_h\gamma)} C^{[-(1-\beta_h k)\gamma-(\lambda-\beta_g k)(1-\gamma)/\delta]} \right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \right.\right.$$
$$\left.\left. (A_Z)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_1 (K_V)^{\frac{1}{\Gamma_1}}}{(1+\phi_h+\phi_g)} - \frac{\Gamma_2 (K_O)^{\frac{1}{\Gamma_1}}}{(1+\phi_h)} \right) \right]^{-1} \right\}^{\frac{\sigma}{\sigma-1}\Gamma_1} \tag{20}$$

By the same method θ_O^* is given by,

$$\theta_O^* = \left\{ (f_O^* - f_V) \left[\left(b^{-\beta_h\gamma} C^{[-(1-\beta_h k)\gamma-(\lambda-\beta_g k)(1-\gamma)/\delta]} \right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \right.\right.$$
$$\left.\left. (A_Z)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_2 (K_O)^{\frac{1}{\Gamma_1}} b^{*-\beta_g(1-\gamma)}}{(1+\phi_h)} - \frac{\Gamma_1 (K_V)^{\frac{1}{\Gamma_1}} b^{-\beta_g(1-\gamma)}}{(1+\phi_h+\phi_g)} \right) \right]^{-1} \right\}^{\frac{\sigma}{\sigma-1}\Gamma_1}. \tag{21}$$

Lastly, I can solve for the θ_V^* by the same method,

$$\theta_V^* = \left\{ (f_V^* - f_O^*) \left[\left(b^{*-\beta_g(1-\gamma)} b^{-\beta_h\gamma} C^{[-(1-\beta_h k)\gamma-(\lambda-\beta_g k)(1-\gamma)/\delta]} \right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \right.\right.$$
$$\left.\left. (A_Z)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_1 (K_V^*)^{\frac{1}{\Gamma_1}}}{(1+\phi_h+\phi_g)} - \frac{\Gamma_2 (K_O^*)^{\frac{1}{\Gamma_1}}}{(1+\phi_h)} \right) \right]^{-1} \right\}^{\frac{\sigma}{\sigma-1}\Gamma_1} \tag{22}$$

As one would expect, each cutoff productivity is increasing in the fixed cost associated with each type of production and decreasing in the fixed cost of the type of production below it on the productivity scale.

II.3.2 Skill intensive industries

The productivity cutoff separating exit from domestic outsourincing is independent of skill intensity, however the other three cutoffs are effected. In a skill intensive industry vertically integrated firms are always more productive than outsourcers. A firm will be a domestic outsourcer until it becomes profitable enough to become a offshore outsourcer therefore a firm indifferent between domestic and foreign outsourcing has a productivity draw which satisfies the following.

$$\frac{\Gamma_2}{(1+\phi_h)} r_O^*(\theta_O^*) - f_O^* = \frac{\Gamma_2}{(1+\phi_h)} r_O(\theta_O^*) - f_O.$$

Substituting my expressions for revenue for $r_O(\theta_O^*)$ and $r_O^*(\theta_O^*)$ I solve for θ_O^* as,

$$\theta_O^* = \left\{ (f_O^* - f_O) \left[\left(b^{-\beta_h \gamma} C^{[-(1-\beta_h k)\gamma - (\lambda - \beta_g k)(1-\gamma)/\delta]} \right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \right.\right.$$
$$\left.\left. (A_Z)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_2 (K_O^*)^{\frac{1}{\Gamma_1}} b^{*-\beta_g(1-\gamma)}}{(1+\phi_h)} - \frac{\Gamma_2 (K_O)^{\frac{1}{\Gamma_1}} b^{-\beta_g(1-\gamma)}}{(1+\phi_h)} \right) \right]^{-1} \right\}^{\frac{\sigma}{\sigma-1}\Gamma_1}. \tag{23}$$

By the same method θ_V is given by,

$$\theta_V = \left\{ (f_V - f_O^*) \left[\left(b^{-\beta_h \gamma} C^{[-(1-\beta_h k)\gamma - (\lambda - \beta_g k)(1-\gamma)/\delta]} \right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \right.\right.$$
$$\left.\left. (A_Z)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_1 (K_V)^{\frac{1}{\Gamma_1}} b^{-\beta_g(1-\gamma)}}{(1+\phi_h+\phi_g)} - \frac{\Gamma_2 (K_O)^{\frac{1}{\Gamma_1}} b^{*-\beta_g(1-\gamma)}}{(1+\phi_h)} \right) \right]^{-1} \right\}^{\frac{\sigma}{\sigma-1}\Gamma_1}. \tag{24}$$

Lastly, I can solve for the θ_V^* by the same method,

$$\theta_V^* = \left\{ (f_V^* - f_V) \left[\left(b^{-\beta_h \gamma)} C^{[-(1-\beta_h k)\gamma - (\lambda - \beta_g k)(1-\gamma)/\delta]} \right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \right.\right.$$
$$\left.\left. (A_Z)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_1 (K_V^*)^{\frac{1}{\Gamma_1}} b^{*-\beta_g(1-\gamma)}}{(1+\phi_h+\phi_g)} - \frac{\Gamma_1 (K_V)^{\frac{1}{\Gamma_1}} b^{-\beta_g(1-\gamma)}}{(1+\phi_h+\phi_g)} \right) \right]^{-1} \right\}^{\frac{\sigma}{\sigma-1}\Gamma_1}. \tag{25}$$

Once again, each cutoff productivity is increasing in the fixed cost associated with each type of production and decreasing in the fixed cost of the type of production below it on the productivity scale.

II.4 Matching, Screening, Employment and Wages

II.4.1 Domestic outsourcer

Firm choice variables under domestic outsourcing can be summarized by matching, screening, hiring, and wages for headquarters employees along with the price and quantity of the production good outsourced. Using the exact productivity cutoffs derived in the previous appendix I can express each firms choice variables as a function of θ/θ_O, b, and underlying parameters. of All of these choice variables can be expressed in terms of the productivity of the least efficient domestic outsourcer θ_O, firm productivity θ and underlying parameters.

Taking the expression for the revenue a domestic outsourcer in equation (**??**) and substituting out θ_O with equation (19) I derive the following expression for the revenue of the least productive domestic outsourcer.[7]

$$r_O \equiv \frac{f_O(1+\phi_h)}{\Gamma_2}.$$

[7] One can arrive at the same expression by simply setting profits equal to zero where profits are defined as $\Pi = \frac{\Gamma_2}{(1+\phi_h)} r_O - f_O$

This then allows me to express firm revenue and all other choice variables as follows:

$$r(\theta) = r_O \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \quad , \qquad r_O \equiv \frac{f_O(1+\phi_h)}{\Gamma_2}$$

$$m_h(\theta) = m_{h^O} \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \quad , \qquad m_{h^O} \equiv \frac{\sigma-1}{\sigma}\frac{\gamma\beta_h}{\Gamma_2}\frac{f_O}{b}$$

$$\alpha_{c,h}(\theta) = \alpha_{c,h^O} \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\delta\Gamma_1}} \quad , \qquad \alpha_{c,h^O} \equiv \left[\frac{\sigma-1}{\sigma}\frac{(1-\beta_h)\gamma}{\Gamma_2}\frac{f_O}{C}\right]^{\frac{1}{\delta}}$$

$$n_h(\theta) = n_{h^O} \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} \quad , \qquad n_{h^O} \equiv {\alpha_{min}}^k \left[\frac{\sigma-1}{\sigma}\frac{\gamma f_O}{\Gamma_2}\right]^{1-k/\delta} \left(\frac{C}{1-\beta_h}\right)^{k/\delta} \frac{\beta_h}{b}$$

$$w_h(\theta) = w_{h^O} \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \quad , \qquad w_{h^O} \equiv \frac{b}{{\alpha_{min}}^k}\left[\frac{\sigma-1}{\sigma}\frac{(1-\beta_h)\gamma}{\Gamma_2}\frac{f_O}{C}\right]^{\frac{k}{\delta}}$$

$$P(\theta) * P_g(\theta) = P_O \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \quad , \qquad P_O \equiv \frac{\sigma-1}{\sigma}\frac{(1-\gamma)f_O}{\Gamma_2}$$

Domestic Intermediate good producer:

$$m_g(\theta) = m_{p^O} \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \quad , \qquad m_{p^O} \equiv \left(\frac{\sigma-1}{\sigma}\right)^2 \frac{(1-\gamma)^2\beta_h}{\Gamma_2(1+\phi_g)}\frac{f_O}{b}$$

$$\alpha_{c,g}(\theta) = \alpha_{c,p^O} \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\delta\Gamma_1}} \quad , \qquad \alpha_{c,p^O} \equiv \left[\left(\frac{\sigma-1}{\sigma}\right)^2 \frac{(\lambda-\beta_g)(1-\gamma)^2}{\Gamma_2(1+\phi_g)}\frac{f_O}{C}\right]^{\frac{1}{\delta}}$$

$$n_g(\theta) = n_{p^O} \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} \quad , \qquad n_{p^O} \equiv {\alpha_{min}}^k \left[\left(\frac{\sigma-1}{\sigma}\right)^2 \frac{(1-\gamma)^2 f_O}{\Gamma_2(1+\phi_g)}\right]^{1-k/\delta} \left(\frac{C}{\lambda-\beta_g}\right)^{k/\delta} \frac{\beta_h}{b}$$

$$w_g(\theta) = w_{p^O} \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \quad , \qquad w_{p^O} \equiv \frac{b}{{\alpha_{min}}^k}\left[\left(\frac{\sigma-1}{\sigma}\right)^2 \frac{(\lambda-\beta_g)(1-\gamma)^2}{\Gamma_2(1+\phi_g)}\frac{f_O}{C}\right]^{\frac{k}{\delta}}$$

II.4.2 Domestic Vertically Integrated Producers

Domestic vertical integration and offshore outsourcing have different expression for revenue depending on the ranking of firms. This difference can be seen in the description of the revenue function. If an industry is non-skill intensive, meaning that $\theta_V < \theta_O^*$, then revenue of a vertically integrated domestic firm can be defined as:

$$r(\theta) = r_V^{S,U} \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}}$$

where, once again I substitute equation (20) into equation (13) in order to express the revenue of a firm with productivity θ_V in terms of underlying parameters as follows,

$$r_V^U \equiv (f_V - f_O)(K_V)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_1 (K_V)^{\frac{1}{\Gamma_1}}}{(1+\phi_h+\phi_g)} - \frac{\Gamma_2 (K_O)^{\frac{1}{\Gamma_1}}}{(1+\phi_h)}\right)^{-1}. \qquad (26)$$

Whereas, if an industry is skill intensive, meaning that $\theta_O^* < \theta_V$, I instead substitute equation (24) into equation (13), then revenue of a vertically integrated domestic firm can be defined as:[8]

$$r_V^S \equiv (f_V - f_O^*)(K_V)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_1 (K_V)^{\frac{1}{\Gamma_1}}}{(1+\phi_h+\phi_g)} - \frac{\Gamma_2 (K_O)^{\frac{1}{\Gamma_1}} \upsilon^{-\beta_g(1-\gamma)(1-\psi_2)}}{(1+\phi_h)} \right)^{-1} \tag{27}$$

As before, having defined revenue as function of parameters and firm productivity I can define all firm choice variables by employing the first order conditions of the firm. For brevity I will use the expression $r_V^{S,U}$ to refer to the expressions in equations (30) and (31) depending the type of industry.

$$\begin{aligned}
m_h(\theta) &= m_h \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} &, \quad m_h &\equiv \frac{\sigma-1}{\sigma}\frac{\gamma\beta_h}{(1+\phi_h+\phi_g)b} r_V^{S,U} \\
m_g(\theta) &= m_g \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} &, \quad m_{pV} &\equiv \frac{\sigma-1}{\sigma}\frac{(1-\gamma)\beta_g}{(1+\phi_h+\phi_g)b} r_V^{S,U} \\
\alpha_{c,h}(\theta) &= \alpha_{c,h^V} \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\delta\Gamma_1}} &, \quad \alpha_{c,h^V} &\equiv \left[\frac{\sigma-1}{\sigma}\frac{(1-\beta_h)\gamma}{(1+\phi_h+\phi_g)C} r_V^{S,U}\right]^{\frac{1}{\delta}} \\
\alpha_{c,g}(\theta) &= \alpha_{c,p^V} \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\delta\Gamma_1}} &, \quad \alpha_{c,p^V} &\equiv \left[\frac{\sigma-1}{\sigma}\frac{(\lambda-\beta_g)(1-\gamma)}{(1+\phi_h+\phi_g)C} r_V^{S,U}\right]^{\frac{1}{\delta}} \\
n_h(\theta) &= n_{h^V} \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} &, \quad n_{h^V} &\equiv \left[\frac{\sigma-1}{\sigma}\frac{\gamma}{(1+\phi_h+\phi_g)} r_V^{S,U}\right]^{1-k/\delta} \frac{{\alpha_{min}}^k \beta_h C^{k/\delta}}{b(1-\beta_h)^{k/\delta}} \\
n_g(\theta) &= n_{p^V} \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} &, \quad n_{p^V} &\equiv \left[\frac{\sigma-1}{\sigma}\frac{1-\gamma}{(1+\phi_h+\phi_g)} r_V^{S,U}\right]^{1-k/\delta} \frac{{\alpha_{min}}^k \beta_g C^{k/\delta}}{b(\lambda-\beta_g)^{k/\delta}} \\
w_h(\theta) &= w_{h^V} \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} &, \quad w_{h^V} &\equiv \frac{b}{{\alpha_{min}}^k}\left[\frac{\sigma-1}{\sigma}\frac{(1-\beta_h)\gamma}{(1+\phi_h+\phi_g)C} r_V^{S,U}\right]^{\frac{k}{\delta}} \\
w_g(\theta) &= w_{p^V} \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} &, \quad w_{p^V} &\equiv \frac{b}{{\alpha_{min}}^k}\left[\frac{\sigma-1}{\sigma}\frac{(\lambda-\beta_g)(1-\gamma)}{(1+\phi_h+\phi_g)C} r_V^{S,U}\right]^{\frac{k}{\delta}}
\end{aligned}$$

II.4.3 Arms-Length Offshore Producers

Once again, offshore outsourcing has different expressions for revenue depending on the skill intensity of the industry. For all firms engaging in offshore outsourcing I can express revenue as a function of productivity and parameters as follows

$$r_O^*(\theta) = r_O^{S,U*} \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}}.$$

If an industry is non-skill intensive, meaning that $\theta_V < \theta_O^*$, then the revenue function will include r_O^{U*}, which is defined as follows,

$$r_O^{U*} \equiv (f_O^* - f_V)(K_O^*)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_2 (K_O)^{\frac{1}{\Gamma_1}}}{(1+\phi_h)} - \frac{\Gamma_1 (K_V)^{\frac{1}{\Gamma_1}} \upsilon^{\beta_g(1-\gamma)(1-\psi_2)}}{(1+\phi_h+\phi_g)} \right)^{-1} \tag{28}$$

whereas, if an industry is skill intensive, meaning that $\theta_O^* < \theta_V$, then the revenue function will include r_O^{S*}, which is defined as follows,

[8] I additionally used the definition of b^* as a function of labor market tightness and the productivity of the X sector in the foreign country to substitute out b^* since $b^* = \zeta_a^{\frac{1}{1+\zeta_b}} {\omega^*}^{\frac{\zeta_b}{1+\zeta_b}}$ and $x^* = \left(\frac{\omega^*}{\zeta_a}\right)^{\frac{1}{1+\zeta_b}}$. Additionally recall that since there are no labor market frictions in the outside sector the expected wage is exactly equal to the marginal productivity of labor, therefore $\omega^* = \upsilon$.

$$r_O^{S^*} \equiv (f_O^* - f_O)(K_O^*)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_2(K_O^*)^{\frac{1}{\Gamma_1}}}{(1+\phi_h)} - \frac{\Gamma_2(K_O)^{\frac{1}{\Gamma_1}}}{(1+\phi_h)} \right)^{-1} \tag{29}$$

I can express the remaining firm specific variables: matching, screening, employment and wages as a function of firm revenue utilizing equations (28) and (29) as follows,

$$m_h(\theta) = m_{hO}^* \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \quad , \quad m_{hO}^* \equiv \frac{\sigma-1}{\sigma} \frac{\gamma\beta_h r_O^{U,S^*}}{(1+\phi_h)b^*}$$

$$\alpha_{c,h}(\theta) = \alpha_{c,hO}^* \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\delta\Gamma_1}} \quad , \quad \alpha_{c,hO}^* \equiv \left[\frac{\sigma-1}{\sigma}\frac{\gamma(1-\beta_h)r_O^{U,S^*}}{(1+\phi_h)C}\right]^{\frac{1}{\delta}}$$

$$n_h(\theta) = n_{hO}^* \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} \quad , \quad n_{hO}^* \equiv \left[\frac{\sigma-1}{\sigma}\frac{\gamma r_O^{U,S^*}}{(1+\phi_h)}\right]^{1-k/\delta} \frac{{\alpha_{min}}^k \beta_h C^{k/\delta}}{b(1-\beta_h)^{k/\delta}}$$

$$w_h(\theta) = w_{hO}^* \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\delta\Gamma_1}} \quad , \quad w_{hO}^* \equiv \frac{b}{{\alpha_{min}}^k}\left[\frac{\sigma-1}{\sigma}\frac{\gamma(1-\beta_h)r_O^{U,S^*}}{(1+\phi_h)C}\right]^{\frac{k}{\delta}}$$

$$P(\theta) * P_g(\theta) = P_O^* \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \quad , \quad P_O^* \equiv \frac{\sigma-1}{\sigma}\frac{(1-\gamma)r_O^{U,S^*}}{(1+\phi_h)}$$

Foreign Intermediate good producer:

$$m_g(\theta) = m_{pO}^* \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \quad , \quad m_{pO}^* \equiv \left(\frac{\sigma-1}{\sigma}\right)^2 \frac{(1-\gamma)^2\beta_h r_O^{U,S^*}}{(1+\phi_g)b}$$

$$\alpha_{c,g}(\theta) = \alpha_{c,pO}^* \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\delta\Gamma_1}} \quad , \quad \alpha_{c,pO}^* \equiv \left[\left(\frac{\sigma-1}{\sigma}\right)^2 \frac{(\lambda-\beta_g)(1-\gamma)^2 r_O^{U,S^*}}{(1+\phi_g)C}\right]^{\frac{1}{\delta}}$$

$$n_g(\theta) = n_{pO}^* \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} \quad , \quad n_{pO}^* \equiv {\alpha_{min}}^k \left[\left(\frac{\sigma-1}{\sigma}\right)^2 \frac{(1-\gamma)^2 r_O^{U,S^*}}{(1+\phi_g)}\right]^{1-k/\delta} \left(\frac{C}{\lambda-\beta_g}\right)^{k/\delta} \frac{\beta_h}{b}$$

$$w_g(\theta) = w_{pO}^* \left(\frac{\theta}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \quad , \quad w_{pO}^* \equiv \frac{b}{{\alpha_{min}}^k}\left[\left(\frac{\sigma-1}{\sigma}\right)^2 \frac{(\lambda-\beta_g)(1-\gamma)^2 r_O^{U,S^*}}{(1+\phi_g)}\right]^{\frac{k}{\delta}}$$

II.4.4 Vertically integrated Offshoring

Vertically integrated offshorers have different expressions for revenue depending on the skill intensity of the industry. For all firms engaging in vertically integrated offshoring I can express revenue as a function of productivity and parameters as follows,

$$r_V^*(\theta) = r_V^{S,U^*}\left(\frac{\theta}{\theta_V^*}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}}$$

If an industry is non-skill intensive, meaning that $\theta_V < \theta_O^*$, then the revenue function will include $r_V^{U^*}$, which is defined as follows,

$$r_V^{U^*} \equiv (f_V^* - f_O^*)(K_V^*)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_1(K_V^*)^{\frac{1}{\Gamma_1}}}{(1+\phi_h+\phi_g)} - \frac{\Gamma_2(K_O^*)^{\frac{1}{\Gamma_1}}}{(1+\phi_h)} \right)^{-1} . \tag{30}$$

whereas, if an industry is skill intensive, meaning that $\theta_O^* < \theta_V$, then the revenue function will include $r_V^{S^*}$, which is defined as follows,

$$r_V^{S*} \equiv (f_V^* - f_V)(K_V^*)^{\frac{1}{\Gamma_1}} \left(\frac{\Gamma_1 (K_V^*)^{\frac{1}{\Gamma_1}} \upsilon^{-\beta_g(1-\gamma)(1-\psi_2)}}{(1+\phi_h+\phi_g)} - \frac{\Gamma_2 (K_V)^{\frac{1}{\Gamma_1}}}{(1+\phi_h+\phi_g)} \right)^{-1} \tag{31}$$

I can express the remaining firm specific variables: matching, screening, employment and wages as a function of firm revenue utilizing equations (30) and (31) as follows,

$$m_h(\theta) = m_{h^V}^* \left(\frac{\theta}{\theta_{O^*}}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \quad , \quad m_{h^V}^* \equiv \frac{\sigma-1}{\sigma} \frac{\gamma \beta_h r_V^{S,U^*}}{(1+\phi_h+\phi_g)b^*}$$

$$m_g(\theta) = m_{p^V}^* \left(\frac{\theta}{\theta_{O*}}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}} \quad , \quad m_{p^V}^* \equiv \frac{\sigma-1}{\sigma} \frac{(1-\gamma)\beta_g r_V^{S,U^*}}{(1+\phi_h+\phi_g)b^*}$$

$$\alpha_{c,h}(\theta) = \alpha_{c,h^V}^* \left(\frac{\theta}{\theta_{O^*}}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\delta\Gamma_1}} \quad , \quad \alpha_{c,h^O}^* \equiv \left(\frac{\sigma-1}{\sigma} \frac{\gamma(1-\beta_h) r_V^{S,U^*}}{(1+\phi_h+\phi_g)C}\right)^{\frac{1}{\delta}}$$

$$\alpha_{c,g}(\theta) = \alpha_{c,p^V}^* \left(\frac{\theta}{\theta_{O^*}}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\delta\Gamma_1}} \quad , \quad \alpha_{c,p^V}^* \equiv \left(\frac{\sigma-1}{\sigma} \frac{(1-\gamma)(\lambda-\beta_g) r_V^{S,U^*}}{(1+\phi_h+\phi_g)C}\right)^{\frac{1}{\delta}}$$

$$n_h(\theta) = n_{h^V}^* \left(\frac{\theta}{\theta_{O^*}}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} \quad , \quad n_{h^V}^* \equiv \left(\frac{\sigma-1}{\sigma} \frac{r_V^{S,U^*}\gamma}{(1+\phi_h+\phi_g)}\right)^{1-k/\delta} \frac{{\alpha_{min}}^k \beta_h C^{k/\delta}}{b(1-\beta_h)^{k/\delta}}$$

$$n_g(\theta) = n_{p^V}^* \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} \quad , \quad n_{p^V}^* \equiv \left(\frac{\sigma-1}{\sigma} \frac{(1-\gamma) r_V^{S,U^*}}{(1+\phi_h+\phi_g)}\right)^{1-k/\delta} \frac{{\alpha_{min}}^k \beta_g C^{k/\delta}}{b(\lambda-\beta_g)^{k/\delta}}$$

$$w_h(\theta) = w_{h^V}^* \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \quad , \quad w_{h^V}^* \equiv \frac{b}{{\alpha_{min}}^k} \left(\frac{\sigma-1}{\sigma} \frac{\gamma(1-\beta_h) r_V^{S,U^*}}{(1+\phi_h+\phi_g)C}\right)^{\frac{k}{\delta}}$$

$$w_g(\theta) = w_{p^V}^* \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \quad , \quad w_{p^V}^* \equiv \frac{b}{{\alpha_{min}}^k} \left(\frac{\sigma-1}{\sigma} \frac{(1-\gamma)(\lambda-\beta_g) r_V^{S,U^*}}{(1+\phi_h+\phi_g)C}\right)^{\frac{k}{\delta}}$$

II.5 Wage Distribution Among Workers

Before I show how changes in the fixed cost of offshoring effect average wages and the wage distribution I will describe the distribution of wages within the economy. This distribution is given by the distribution of wages, for both production and headquarter services, across firms of different organizational forms, $G_{w_j,O}(w)$, $G_{w_j,V}(w)$, $G^*_{w_j,O}(w)$ and $G^*_{w_j,V}(w)$, weighted by the share of employment of each type of firm, $\mathcal{S}_{n_j,O}$, $\mathcal{S}_{n_j,V}$, $\mathcal{S}^*_{n_j,O}$ and $\mathcal{S}^*_{n_j,V}$, for $j \in \{h, p\}$

I will describe in detail the case of a non-skill intensive industry first. The share of workers employed in the G sector in firms who are independently owned suppliers is given by $\mathcal{S}_{n_g,O}$ which can be written as,

$$\mathcal{S}_{n_g,O} = \frac{s_{n_g,O}}{s_{n_g,O} + s_{n_g,V}}$$

where,

$$s_{n_g,O} = \int_{\theta_O}^{\theta_V} n_g(\theta) dG_\theta(\theta), \qquad s_{n_g,V} = \int_{\theta_V}^{\theta_{O^*}} n_g(\theta) dG_\theta(\theta)$$

recalling the previous expressions for n_g derived above appendix II.4.1 and II.4.2 and imposing the assumption of Pareto distribution I have the following,

$$S_{n_g,O} = \int_{\theta_O}^{\theta_V} n_{p^O} \left(\frac{\theta}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} \xi \left(\frac{\theta_{min}^\xi}{\theta^{\xi+1}}\right) \quad \text{and} \quad S_{n_g,V} = \int_{\theta_V}^{\theta_O^*} n_{p^V} \left(\frac{\theta}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1-\frac{k}{\delta})} \xi \left(\frac{\theta_{min}^\xi}{\theta^{\xi+1}}\right),$$

which can be simplified to the following,

$$s_{n_g,O} = n_{p^O} \frac{\theta_{min}^{\xi}}{\theta_O^{\vartheta_1+\xi}} \left[\frac{\left(1 - \frac{\theta_O}{\theta_V}^{\vartheta_1}\right)}{\vartheta_1} \right], \quad \text{and} \quad s_{n_g,V} = n_{p^V} \frac{\theta_{min}^{\xi}}{\theta_V^{\vartheta_1+\xi}} \left[\frac{\left(1 - \frac{\theta_V}{\theta_{O*}}^{\vartheta_1}\right)}{\vartheta_1} \right]$$

where $\vartheta_1 \equiv \xi - \frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1 - \frac{k}{\delta}) > 0$.

The distribution of wages across workers employed by arms-length suppliers of production intermediates at home ($G_{w_g,O}(w)$), is proportional to the fraction of workers receiving a wage $w(\theta) \in \left[w_{p^O}, w_{p^O}\left(\frac{\theta_V}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}\right]$, is proportional to $n_g(\theta)dG_\theta(\theta)$. This gives the following representation for $G_{w_g,O}(w)$,

$$G_{w_g,O}(w) = \frac{\int_{\theta_O}^{\theta_{w_g,O}(w)} n_g(\theta)dG_\theta(\theta)}{\int_{\theta_O}^{\theta_V} n_g(\theta)dG_\theta(\theta)} = \frac{\int_{\theta_O}^{\theta_{w_g,O}(w)} n_g(\theta)dG_\theta(\theta)}{s_{n_g,O}}$$

where $\theta_{w_g,O}(w)$ is the inverse of $w(\theta)$ which is given by $\theta_{w_g,O}(w) = \theta_O \left(\frac{w}{w_{p^O}}\right)^{\frac{\sigma}{\sigma-1}\frac{\delta\Gamma_1}{k}}$. Imposing the assumption of Pareto distribution I have the following expression for $G_{w_g,O}(w)$,

$$G_{w_g,O}(w) = \frac{1 - \left(\frac{w_{p^O}}{w}\right)^{\vartheta_2}}{\left(1 - \frac{\theta_O}{\theta_V}^{\vartheta_1}\right)} \quad \text{for} \quad w \in \left[w_{p^O}, w_{p^O}\left(\frac{\theta_V}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}\right], \tag{32}$$

where $\vartheta_2 \equiv \frac{\sigma}{\sigma-1}\frac{\delta\Gamma_1}{k}(\xi - \frac{\sigma-1}{\sigma}\frac{1}{\Gamma_1}(1 - \frac{k}{\delta}))$.[9]

The distribution of wages across workers employed by vertically integrated suppliers of production intermediates at home $G_{w_g,V}(w)$, is proportional to the fraction of workers receiving a wage $w(\theta) \in \left[w_{p^V}, w_{p^V}\left(\frac{\theta_O^*}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}\right]$, is proportional to $n_g(\theta)dG_\theta(\theta)$, which yields,

$$G_{w_g,V}(w) = \frac{1 - \left(\frac{w_{p^V}}{w}\right)^{\vartheta_2}}{\left(1 - \frac{\theta_V}{\theta_{O*}}^{\vartheta_1}\right)} for \quad w \in \left[w_{p^V}, w_{p^V}\left(\frac{\theta_O^*}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}\right] \tag{33}$$

Both 32 and 33 are truncated Pareto distributions, with shape parameter ϑ_2 and lower support w_{p^O} and w_{p^V} respectively. These expressions combined give use the domestic wage distribution for production workers across all firms, $G_w(w)$

$$G_{w_g}(w) = \begin{cases} \mathcal{S}_{n_g,O}G_{w_g,O}(w) & \text{for} \quad w_{p^O} \leq w \leq w_{p^O}\left(\frac{\theta_V}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \\ \mathcal{S}_{n_g,O} & \text{for} \quad w_{p^O}\left(\frac{\theta_V}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \leq w \leq w_{p^V}, \\ \mathcal{S}_{n_g,V}G_{w_g,V}(w) & \text{for} \quad w_{p^V} \leq w \leq w_{p^V}\left(\frac{\theta_O^*}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \end{cases}$$

[9]For the mean and variance of the wage distribution to be finite the following condition must hold: $\xi\Gamma_1 > \frac{\sigma-1}{\sigma}(1 - \frac{k}{\delta})$. This condition places a lower bond on the skewness of the productivity distribution, which is governed by ξ.

The exact same procedure is done to find $G_{w_h}(w)$

$$G_{w_h}(w) = \begin{cases} \mathcal{S}_{n_h,O} G_{w_h,O}(w) & \text{for} \quad w_{h^O} \leq w \leq w_{p^O} \left(\frac{\theta_V}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \\ \mathcal{S}_{n_h,O} & \text{for} \quad w_{h^O} \left(\frac{\theta_V}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \leq w \leq w_{h^V}, \\ \mathcal{S}_{n_h,V} G_{w_h,V}(w) & \text{for} \quad w_{h^V} \leq w \leq w_{p^V} \left(\frac{\theta_O^*}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \\ \mathcal{S}_{n_h,V} & \text{for} \quad w_{h^V} \left(\frac{\theta_O^*}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \leq w \leq w_{h^O}^*, \\ \mathcal{S}_{n_h,O}^* G_{w_h,O}^*(w) & \text{for} \quad w_{h^O}^* \leq w \leq w_{p^O}^* \left(\frac{\theta_V}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \\ \mathcal{S}_{n_h,O}^* & \text{for} \quad w_{h^O}^* \left(\frac{\theta_V}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \leq w \leq w_{h^V}^*, \\ \mathcal{S}_{n_h,V}^* G_{w_h^*,V}(w) & \text{for} \quad w_{h^V}^* < w, \end{cases}$$

Lastly, for skill intensive industries the distribution of wages among workers differs due to the different sort of firms into organizational form based on productivity. For skill intensive industries the distribution of wages can be summarized as follows,

$$G_{w_g}(w) = \begin{cases} \mathcal{S}_{n_g,O} G_{w_g,O}(w) & \text{for} \quad w_{p^O} \leq w \leq w_{p^O} \left(\frac{\theta_O^*}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \\ \mathcal{S}_{n_g,O} & \text{for} \quad w_{p^O}^* \left(\frac{\theta_V}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \leq w \leq w_{p^V}, \\ \mathcal{S}_{n_g,V} G_{w_g,V}(w) & \text{for} \quad w_{p^V} \leq w \leq w_{p^V} \left(\frac{\theta_V^*}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \end{cases}$$

The exact same procedure is done to find $G_{w_h}(w)$

$$G_{w_h}(w) = \begin{cases} \mathcal{S}_{n_h,O} G_{w_h,O}(w) & \text{for} \quad w_{h^O} \leq w \leq w_{p^O} \left(\frac{\theta_O^*}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \\ \mathcal{S}_{n_h,O} & \text{for} \quad w_{h^O} \left(\frac{\theta_O^*}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \leq w \leq w_{h^O}^*, \\ \mathcal{S}_{n_h,O}^* G_{w_h,O}^*(w) & \text{for} \quad w_{h^O}^* \leq w \leq w_{p^O}^* \left(\frac{\theta_V}{\theta_O^*}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \\ \mathcal{S}_{n_h,O}^* & \text{for} \quad w_{h^O}^* \left(\frac{\theta_V}{\theta_O}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \leq w \leq w_{h^V}^*, \\ \mathcal{S}_{n_h,V} G_{w_h,V}(w) & \text{for} \quad w_{h^V} \leq w \leq w_{h^V} \left(\frac{\theta_V^*}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}}, \\ \mathcal{S}_{n_h,V} & \text{for} \quad w_{p^V} \left(\frac{\theta_V^*}{\theta_V}\right)^{\frac{\sigma-1}{\sigma}\frac{k}{\delta\Gamma_1}} \leq w \leq w_{h^V}^*, \\ \mathcal{S}_{n_h,V}^* G_{w_h^*,V}(w) & \text{for} \quad w_{h^V}^* < w, \end{cases}$$