Supplemental Appendix: The Missing Middle Managers: Labor Costs, Firm Structure, and Development*†

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A Data Details

This appendix provides further details on data sources and empirical results.

A.1 Data Composition: Raw Data and Selected Sample

Table A.1 gives an overview of the Company database. The first row shows the raw data as it comes to us from the Company. The columns under the subheading total show the number of observations and the number of workers covered in total. The distinction between the two arises because the Company records the average pay and number of workers for each firm-job-location-year. In total, the Company's database covers just over 500,000 firm-job-location-year observations that correspond to just over 1 million workers.

The next two columns describes the composition of the sample in terms of the location of the affiliate, which is where the workers work. We focus on whether the affiliate is in a developing and emerging country, defined as having GDP per worker less than 10 percent of the U.S. level in 2017. About two-thirds of the total sample comes from such countries. The last two columns describe the sample composition in terms of whether the parent of the affiliate is headquartered in a developed country, defined as having GDP per worker greater than 50 percent of the U.S. level in 2017. Roughly three-fourths of the total sample comes from foreign affiliates of such multinational organizations.

TABLE A.1: SAMPLE SELECTION AND OBSERVATIONS (THOUSANDS)

	Total		Affiliate in Developing		HQ in Developed	
	Obs	Workers	Obs	Workers	Obs	Workers
Raw Data	507	1,024	314	694	399	790
Selected Sample	170	321	93	170	107	182

Table gives sample size for the raw data and the subsample used for results that drops non-profits and governments. "Total" captures all observations, "Affiliate in Developing" captures observations from affiliates in countries with GDP per capita less than 10 percent of the United States, and "HQ in Developed" captures affiliates whose parent firms are headquartered in countries with GDP per capita greater than 50 percent of the United States. For each, obs counts the number of firm-job-location-years and workers counts the number of employees.

Our main sample restriction is to focus on for-profit firms, discarding charities and governmental organization. The second row of Table A.1 repeats the same calculations for our chosen subsample. Roughly one-third of the Company's database comes from for-profit firms. Among our subsample, a little more than half of the observations come from affiliates in developing and emerging countries, and a little more than half of the observations come from affiliates whose parent firm is headquartered in developed countries.

A.2 Representative Data Sources and Comparisons

The Company's database covers a very particular population of jobs and firms – managers and business professionals at modern business enterprises. It is not well suited for studying typical firms or their workers in developing countries because those firms do not engage the Company's services and so do not appear in the Company's database. We assemble nationally representative data sets to study employment patterns and compensation among such firms for context.

We start by comparing the employment patterns in terms of occupations. We map Company job titles to 1-digit ISCO-08 occupations. We draw on representative data from the ILOSTAT database (International Labour Organization, 2022). The database includes tabulations of workers employed by ISCO-08 2-digit occupation category. We aggregate to the 1-digit level.

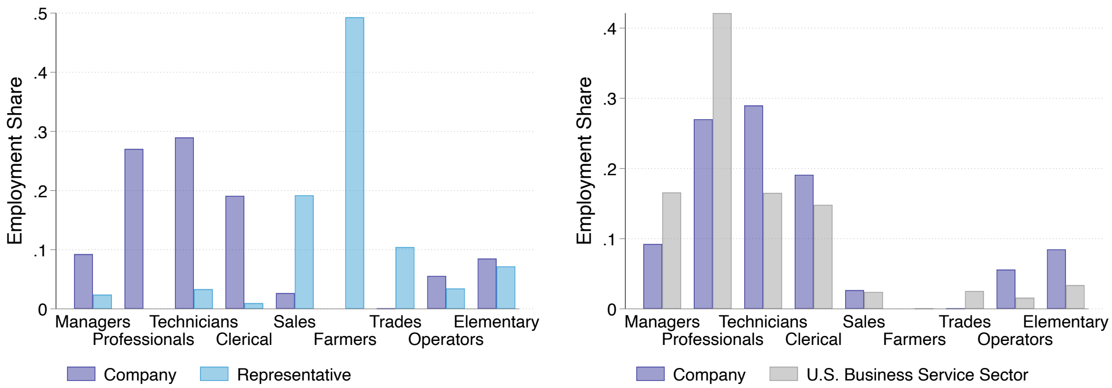
Figure A.1a compares the occupational distribution in the Company database and representative data for countries with GDP per worker less than $5,000 in 2017 U.S. dollars. The two are starkly different: the Company database consists almost entirely of managers, professionals, technicians, and clerks, whereas representative data are dominated by sales workers and farmers.

As a second point of comparison, we compare the same Company data to the U.S. business service sector. We use 2013–2017 American Community Survey microdata from Ruggles *et al.* (2023). We focus on employed 16–70 year olds with non-zero weights and valid responses to key questions. We limit attention to workers in the business service sector, which is defined as the industries: accounting, tax preparation, bookkeeping and payroll services; computer systems design and related services; management, scientific and technical consulting services; scientific research and development services; advertising and related services; management of companies and enterprises; employment services; and business support services. We use the crosswalk provided by the Census Bureau to assign the original SOC occupation codes to ISCO-08 1-digit equivalents. We compute the employment share of workers by 1-digit ISCO occupation using the appropriate weights (perwt).

Figure A.1b shows that the distribution of employment across occupations in the Company database (still in developing countries) is much closer to the distribution in the U.S. business service sector. This helps provide context for the types of jobs and firms that are covered by the database.

FIGURE A.1: OCCUPATIONAL DISTRIBUTION OF COMPANY DATA

(a) Developing Countries (Representative) (b) U.S. Business Service Sector



Note: Company data represent average distribution among countries with 2017 GDP per worker less than $5,000.

Our second goal is to compare the earnings of middle managers and production workers in the Company database to earnings of the same workers in representative data. Published ILO tabulations do not provide average earnings by country and occupation. Instead, we draw on microdata that contain information on earnings and occupation for four countries spanning a wide range of the income distribution: Rwanda, Bangladesh, Bolivia, and the United States, which have 2017 GDP per worker of $2,300, $4,600, $7,300, and $124,000. We select the first three because they are developing countries with nationally representative labor force surveys that report information on earnings and occupation. We use the United States as a natural benchmark.

Our data source for Rwanda is the 2024 Labor Force Survey, which is a representative sample of 14,752 households in 2024 (National Institute of Statistics of Rwanda (NISR) - Ministry of Finance and Economic Planning (MINECOFIN), 2024). Our data source for Bangladesh is the 2013 Labour Force and Child Labour Survey, which is a representative sample of 36,242 households in 2013 (Bangladesh Bureau of Statistics (BBS), 2013). Our data source for Bolivia is the 2015–2018 rounds of the quarterly Encuesta Continua de Empleo, a nationally representative labor force survey spanning several years (Instituto Nacional de Estadística, Estado Plurinacional de Bolivia, 2015–2018). Our data source for the United States is again the 2013–2017 American Community Survey (Ruggles *et al.*, 2023).

In all four countries we focus on employed wage workers who are 16–70 years old, work outside the agricultural industry, and report positive earnings. We categorize middle managers using occupational codes. Rwanda, Bangladesh, and Bolivia collect data on monthly earnings. We annualize by multiplying this figure by 12. The United States collects data on annual earnings. We convert all figures to 2017 U.S. dollars by adjusting for wage growth as we did for the Company data and then applying the nominal exchange rate, which we derive from World Bank (2025).

We start by comparing mean earnings. We compute the weighted mean of log earnings by country and middle manager status, then exponentiate the figure. In all cases we divide through by non-agricultural GDP per worker, which we construct using data from World Bank (2025). We use non-agricultural GDP because most agricultural workers are self-employed and do not report earnings in our microdata. Further, it is well-known that agricultural workers have lower earnings, particularly in developing countries, so this restriction makes our earnings and productivity figures more comparable (Gollin *et al.*, 2014).

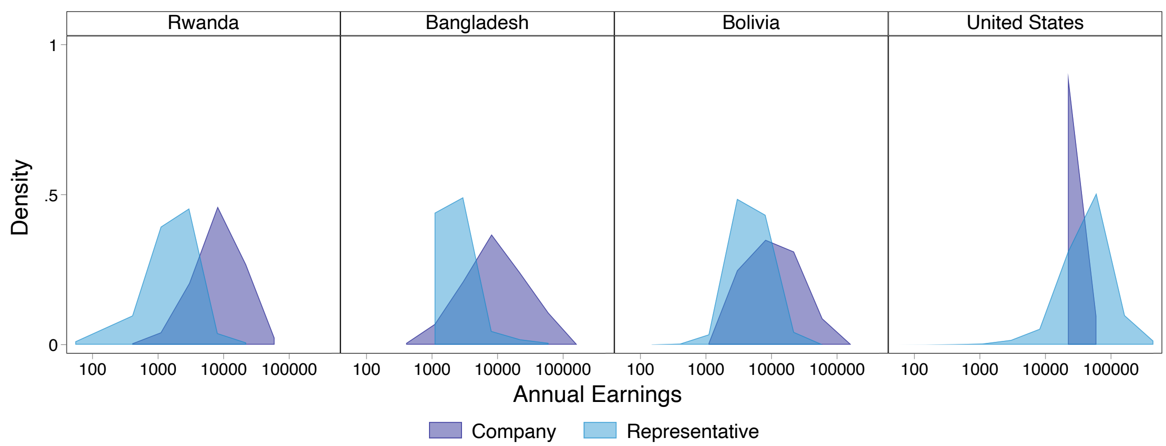
TABLE A.2: LABOR EARNINGS BY OCCUPATION AND SOURCE

	Managers		Non-Managers	
	Company	Representative	Company	Representative
Country				
Rwanda	7.14	0.77	2.14	0.20
Bangladesh	5.68	0.56	0.97	0.31
Bolivia	3.37	0.95	0.74	0.55
United States	0.40	0.60	0.27	0.32

Company refers to findings for modern firms in the Company's database described in section I. Representative refers to findings for all firms from representative data sources described in appendix A. All figures are earnings relative to non-agricultural GDP per worker.

Table A.2 shows the relative earnings for each country. There are three main findings. First, the Company database and the nationally representative data sets agree closely on compensation in the United States. This reflects a combination of the fact that modern firms are common and the fact that modern-traditional pay gaps for managers are not too large in the United States. Second, compensation is much higher in the Company database than the nationally representative data sets for the developing countries. Third, this gap is much larger for managers than for production workers.

FIGURE A.2: DISTRIBUTION OF MIDDLE MANAGEMENT COMPENSATION



We then compare the distributions of earnings between the representative and Company data. For the representative data, we focus on college-educated middle managers; for the Company data, we focus on middle managers. Figure A.2 shows the results as overlapping histograms, with the countries arranged in order of development. The findings confirm those in Table A.2. For the United States, the representative and Company data have a similar median, although the representative data are slightly more right skewed. Moving to the left (lower GDP per capita), the distribution of earnings in the representative data shift left faster than the distribution of earnings in Company data. Put differently, the Company data draw from an increasingly selected portion of the overall distribution, such that the median of the Company distribution corresponds to the 94th percentile of the representative Bolivian distribution, the 97th percentile of the Bangladeshi distribution, and the 99th percentile of the Rwandan distribution.

A.3 Additional Results on Variation by Skill Levels

This appendix provides additional results on how compensation and hiring patterns vary by skill level. First, we document that the patterns on compensation by skill level apply also when we limit our attention to domestic firms. Table A.3 shows the estimates by skill group for domestic firms, analogous to Table 2 in the main text. Both qualitatively and quantitatively the results are similar to those that apply for all firms as documented in the text.

TABLE A.3: ESTIMATED ELASTICITY OF COMPENSATION BY SKILL LEVEL: DOMESTIC FIRMS

	All	By Skill Level			
		Non-Management	Low	Medium	High
Log GDP per worker	0.241***	0.310***	0.256***	0.202***	0.145***
	(0.018)	(0.020)	(0.035)	(0.007)	(0.008)
Fixed Effects	Year × Job	Year × Job	Year × Job	Year × Job	Year × Job
R-squared	0.704	0.473	0.355	0.291	0.272
N	34,374	3,073	16,272	9,441	5,588
Example Job		Driver	Secretary	Accountant	Senior Executive

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We then provide evidence on how the mix of workers hired by clients in the Company database varies with respect to relative prices. We regress three different measures of workforce composition on the appropriate measures of relative prices to see whether clients engage in any substitution in response to the large measured relative price variation.

For our first approach we use the fact that the Company gives each job a skill level and ask whether the job levels respond to the relative price of management. We standard normalize the measure of job level to give it interpretable units. We measure the relative cost of management as the log average compensation in the Company database net of the estimated effect of job and year fixed effects minus the log of GDP per worker. Table A.4 column (1) shows the estimates: higher relative costs of management are associated with slightly higher average levels of workers, meaning more skilled and highly compensated workers. Column (4) shows the results from the same specification with firm-year interactions. This specification leverages variation in hiring patterns across affiliates within a given firm. The estimated effect is similar. Both specifications yield results that are economically and statistically insignificant.

For our second and third approaches we estimate how relative hiring patterns respond to relative wages. In the second approach we use a linear probability model to estimate the effect of the relative cost of management on the probability a worker is a manager. The relative cost of management is the average log compensation of managers in the Company database minus the average compensation of non-managers in the Company database, where each measure of compensation is net of the estimated effect of job and

TABLE A.4: RESPONSE OF HIRING PATTERNS TO RELATIVE WAGES

	Aggregate			Within Firm		
	Level	Managers	Top Managers	Level	Managers	Top Managers
Wage/GDP per worker	0.0112			0.00977		
	(0.0625)			(0.0134)		
Manager Wage		-0.159			0.00284	
		(0.0838)			(0.0110)	
Top Wage			-0.0633			0.0200
			(0.0583)			(0.0267)
R-squared	0.000	0.019	0.001	0.266	0.335	0.143
N	162,465	162,114	151,967	162,460	162,109	151,962

Level is standard normalized job level from Company's internal scheme. Manager is a dummy for workers with manager rather than non-manager positions, while top managers is a dummy for workers with a medium or high-skilled manager position as compared to a low-skill one (as in Table 2). Wages are the logarithm of relative wage for the corresponding groups in the Company database. Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

year fixed effects. As columns (2) and (5) show, there is no economically or statistically significant effect of manager compensation on the share of managers

Finally, for the third approach we use a linear probability model to estimate the effect of the relative cost of managers with an above median versus below median level on the probability that a manager has above median skills. In this case we take the global distribution of skills and define a fixed, global cutoff for which managers are above versus below median. The relative cost of above-median managers is the average log compensation of above median managers minus the relative log compensation of below median managers, where each measure of compensation is net of the estimated effect of job and year fixed effects. As columns (3) and (6) show, there is again no economically or statistically significant effect of the price of above-median managers on the share of above-median managers.

We emphasize again that the Company's database is an incomplete record of its clients' hiring patterns. In particular it contains few production and supervisory workers, and so the results in columns (2) and (5) should be treated with caution. Among the workers captured, there is no evidence of substitution to cheaper, less skilled workers, either at the aggregate or across affiliates within a given firm, despite large differences in relative costs.

B Robustness Checks on Quantitative Results

This section describes robustness checks related to the quantitative importance of factor costs for technology adoption decisions.

B.1 Extension: Beyond Cobb-Douglas

This section extends our analysis beyond the Cobb-Douglas framework to provide a more general characterization of how factor costs affect technology adoption. As before, each good can be produced using a traditional and a modern technology. Production functions are given by

$$y^T(i) = A^T(i) f^T(x_1^T(i), \ldots, x_F^T(i)),$$
$$y^M(i) = A^M(i) f^M(x_1^M(i), \ldots, x_F^M(i)),$$

where f^T and f^M are general production functions satisfying standard properties. The modern technology is used when

$$\frac{A^M(i)}{A^F(i)} > \frac{c_M(w_1, \ldots, w_F)}{c_T(w_1, \ldots, w_F)},$$

where c_T and c_M are the unit cost functions associated with the production functions f^T and f^M. To analyze the impact of changes in factor costs, we note that the change in relative unit costs satisfy

$$\frac{d \log \frac{c_M}{c_T}}{d \log w_f} = \alpha_f^M(w_1, \ldots, w_F) - \alpha_f^T(w_1, \ldots, w_F),$$

where α_f^M and α_f^T are the factor compensation shares of f in the modern and traditional technology. Note that this formula coincides with the Cobb-Douglas setup, with the one difference that factor shares are now functions of factor prices, rather than constants. This means that the effect on relative unit costs, and hence adoption, of a change in a factor price $\Delta \log w_f = \log(w_f^1 / w_f^0)$ is given by

$$\Delta \log \frac{c_M}{c_T} = \int_{w_f^0}^{w_f^1} [\alpha_f^M(w_1, \ldots, w_f', \ldots w_F) - \alpha_f^T(w_1, \ldots, w_f', \ldots w_F)] d \log w_f'.$$

When the production function is Cobb-Douglas, factor shares are independent of factor prices and we recover $(\alpha_f^M - \alpha_f^T)\Delta \log w_f$ as before. In the general case, there is an additional effect coming from factor shares changing, with the effect being stronger if the modern-traditional share difference expands with the price change, and the effect being weaker if the modern-traditional share shrinks. We use these insights in our sensitivity analysis.

B.2 Sensitivity Analysis

The extended framework shows that we can test for and quantify the importance of deviating from the Cobb-Douglas assumption by examining the information provided by factor shares. For our purposes, the key question is whether and to what extent factor shares differ between developing and developed economies given the large difference in relative factor prices.

To find a consistent set of modern firms in rich and poor countries, we use data from the Bureau of Economic Analysis on business activities of majority-owned foreign affiliates of U.S. multinational enterprises. Until 2007, they collected data on total labor compensation and compensation of managerial, professional, and technical labor by country of affiliate. We use data from 2004, the last benchmark year with this breakdown (Bureau of Economic Analysis, 2004, Table III.H 1). On average, 49 percent of compensation goes to managerial, professional, and technical workers. This figure is higher than for average French firms in Caliendo *et al.* (2015), reflecting the fact that multinational affiliates are typically more skill-intensive. Multinational affiliates also have very low labor shares, around 10% of sales, partly because they often serve as local sales operations. While multinationals differ in the *level* of factor shares, the shares remain relatively stable across income levels, despite large relative price movements. For the 53 countries with both compensation statistics and real GDP data, the correlation between log GDP per worker and the management share of compensation is only 0.16. A regression of management compensation shares on log GDP per worker predicts only a 6 percentage point difference between the richest and poorest countries. This evidence suggests that a constant management share is a reasonable approximation, supporting our use of the Cobb-Douglas assumption for management.

B.3 Extension: Heterogeneous Labor Intensity

To build intuition, start with the Cobb-Douglas framework developed in Section III.A and assume that both modern and traditional production face the same non-labor costs, $P_M = P_T = P$. We allow each sector to face heterogeneous labor intensity $s_{L,T}$ and $s_{L,M}$ and assume that $s_{L,T} > s_{L,M}$. The industries that choose modern production is given by:

$$\frac{z_{i,M}}{z_{i,T}} \geq e^{\tau} \left(\frac{w_m}{w_p}\right)^{(\alpha_M-\alpha_T)s_{L,M}} \left[\frac{w_p^{1-\alpha_T} w_m^{\alpha_T}}{P}\right]^{s_{L,M}-s_{L,T}}.$$

There are three terms on the right-hand side. The first captures the effect of distortions. The second captures the relative cost of management interacted with the relative management intensity of modern production. This is the term that we quantify in our main analysis. The third term captures the additional effect of allowing for heterogeneous labor intensity.

This interpretation of this term is very similar to that of the second term. We have assumed that traditional production is more labor-intensive than modern production, which implies that modern production must be more intensive in the other factors, whose cost is captured by P. This term captures the relative cost of the other factors to labor interacted with the difference in relative factor intensity – in this case, between labor and other factors. Generally, labor is more expensive relative to other inputs in developed countries. Given this, allowing for $s_{L,T} > s_{L,M}$ would imply that the third, novel term is increasing with development, generating an additional force for the adoption of modern technologies in developed countries.

This same logic carries over to the general framework of Section B.1. Label the first two factors as management and production labor. Then we can derive

$$\begin{aligned}
\frac{d\log\frac{c_M}{c_T}}{dy} &= \left[s_{M,m}(\Theta) - s_{T,m}(\Theta)\right]\frac{d\log(w_m/w_p)}{dy} \\
&\quad + \left[s_{M,m}(\Theta) + s_{M,p}(\Theta) - s_{T,m}(\Theta) - s_{T,p}(\Theta)\right]\frac{d\log(w_p)}{dy} \\
&\quad + \sum_{f=3}^{F}\left[s_{M,f}(\Theta) - s_{T,f}(\Theta)\right]\frac{d\log(\Theta_f)}{dy}.
\end{aligned}$$

This expression decomposes the effect of a marginal change in development on the relative cost of operating a modern firm into three terms. The first term captures the interaction between relative management intensity of modern production and the effect of development on the relative cost of management. The second term captures the interaction between relative labor intensity of modern production and the effect of development on labor cost. The third term captures the interaction between the relative intensity of modern production in all other factors and the effect of development on their costs.

If modern and traditional production have the same labor share, then $s_{M,m}(\Theta) + s_{M,p}(\Theta) = s_{T,m}(\Theta) + s_{T,p}(\Theta)$ and the second term drops out of the expression. If instead traditional production is more labor intensive, then $s_{M,m}(\Theta) + s_{M,p}(\Theta) - s_{T,m}(\Theta) - s_{T,p}(\Theta) < 0$. Since wages rise with development, $\frac{d\log(w_p)}{dy} > 0$ and this force tends to push for lower relative costs in the modern sector. At the same time, modern production must then put a higher weight on the remaining, non-labor factors. However, as long as the price of labor rises faster than the weighted average of non-labor factors with development, then it remains the case that heterogeneous labor intensity is a force that lowers the relative cost of modern production in developed countries and hence helps explain why developed countries have more modern production.

B.4 Comparison to Other Factor Costs

To put our quantitative findings in perspective, we compare them against two other factor costs studied in the literature: electricity and financing costs. Applying a similar methodology, we find that management costs are a greater barrier to modern firms than either the cost of replacing generator-produced electricity with grid-based electricity or the effect of reducing credit spreads from Brazilian levels (45%) to US levels (5%).

Electricity prices. For electricity, we model a price reduction equivalent to fully replacing generator-produced electricity with grid-based electricity. We base our numbers on the study by Fried & Lagakos (2023) of electricity use by firms in Sub-Saharan Africa. They find that firms with generators produce 59% of their electricity at 5.51 times the average cost of grid-based electricity (Fried & Lagakos, 2023, Online Appendix, Table C.1). The higher costs reflect both variable costs ($0.28/kWh vs $0.06/kWh) and maintenance and capital costs for generators ($0.08/kWh), all in 2014 dollars.

We define the price shock of eliminating generator dependence as:[1]

$$\Delta \log w_{electricity} = \log \left(\frac{0.06 \times (1 - 0.59) + 0.59 \times 0.34}{0.06} \right) = 1.32.$$

For the electricity factor share, we set $\alpha^M_{electricity}$=0.035, derived by multiplying Lagakos and Fried's estimate of electricity's value-added share in the modern sector (0.07) with an intermediate input share of 0.5. Consistent with their assumption that traditional firms do not use electricity, we set $\alpha^T_{electricity} = 0$. These figures yield a total cost shifter of 1.32 $\times$ 0.035 = 4.6 log points, as compared to 21 log points for management costs.

Financing costs. To model financial frictions, we examine the impact of reduced credit spreads on factor prices facing modern firms. Our experiment considers a fall in credit spreads from 45 to 5 percentage points. This calibration draws on Cavalcanti *et al.* (2023), who analyze a comprehensive loan-level data from a credit registry in Brazil. The initial 45 percentage point spread represents the credit-weighted average of credit spreads in their study, while the 5 percentage point endpoint is an estimate of US credit spreads based on the difference between the US high-yield index and the market yield on 10-year U.S. treasury securities (2015 values).

To calculate the resulting decrease in capital costs, we follow Cavalcanti *et al.* (2023) in assuming a risk-free rate of 2.5% and a depreciation rate of 3%, implying a reduction in capital user costs $\log \frac{0.025+0.03+0.45}{0.025+0.03+0.05} = 1.57$. For the cost share of external financing in the modern sector, we set $\alpha^M_{ext} = 0.085$. This estimate combines three factors: a capital share of value added (0.33) from Cavalcanti et al., an intermediate input share of gross output (0.5), and an estimated external financing share in modern firms (0.4). Our external financing share estimate is an upper bound based on Cavalcanti et al.'s finding that 19% of the capital stock is externally financed. Conservatively assuming no external financing for traditional firms and at least 50% of the aggregate capital stock in modern firms (as a comparison, the top 10% of firms have 77% of employment), we deduce that the external financing share in modern firms cannot exceed 0.4. Finally, we set the share of external financing in traditional firms to zero. This choice maximizes the difference to the modern sector, creating a best-case scenario for financial frictions to influence the adoption of modern technologies. These figures yield a total cost shifter of 1.57 $\times$ 0.085 = 13 log

[1] This calculation assumes that the aggregate self-generation share equals that found for firms with generators. In reality, 18% of modern firms lack generators, which would imply a smaller initial self-generation share and thus a smaller price shock if adjusted for.

points.

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