Online Appendix for:

The Declining Worker Power Hypothesis: An explanation for the recent evolution of the American economy

Anna Stansbury and Lawrence H. Summers
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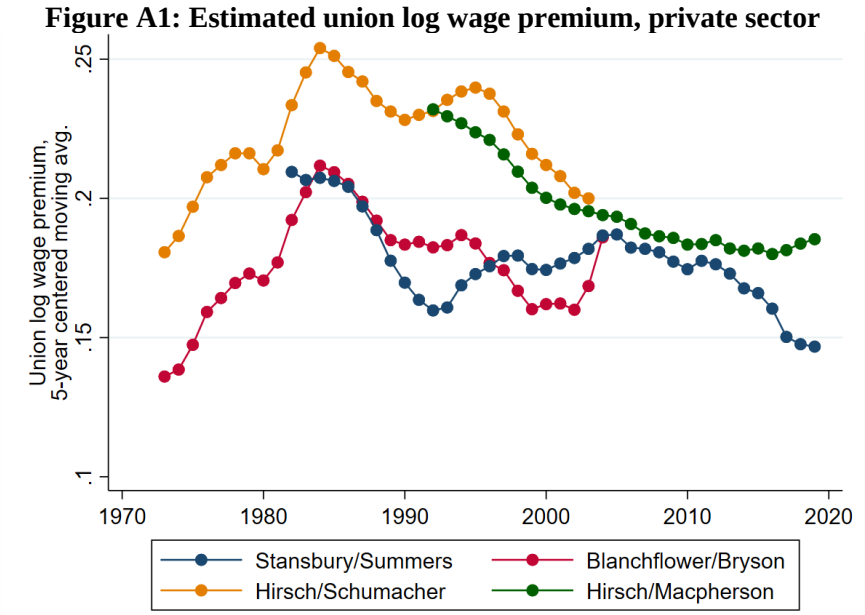
Appendix A: Estimation of wage premia

A.1. Estimating the union wage premium in the CPS-ORG

Following Hirsch and Macpherson (2019), we estimate the union wage premium using the CPS-ORG over 1984-2019. All the CPS data sets used in this paper are downloaded from IPUMS (Flood et al 2020). We restrict the sample to private sector workers, and we also drop workers for whom wages were imputed in the CPS (following Bollinger and Hirsch (2006). We do this because the wage imputation procedure in the CPS does not take union status into account, which biases estimates of the union wage premium downwards). Our key variable of interest – union status – is a dummy variable which takes the value 1 if the worker was either a member of a union or covered by a collective bargaining agreement. We construct our dependent variable – hourly wage – as either the hourly wage reported by the worker, or the weekly earnings divided by usual hours worked at the respondent's main job (if hourly wage was not reported). We then regress the log hourly wage on union status and various control variables: age, age squared, male dummy, 6 race categories, Hispanic dummy, age # male, age squared # male, married dummy, married # male, state, dummy for central city, 6 education categories, education # age, education # age squared, education # male, dummy for full-time workers, dummies for 383 occupation categories, and for 250 industry categories (where # denotes an interaction). We run our regressions separately for each year, estimating a separate union wage premium for each year. Our estimates are shown in Figure A1 alongside estimates from Hirsch and Schumacher (2004), Blanchflower and Bryson (2004), and Hirsch and Macpherson (2019).

Figure A1: Estimated union log wage premium, private sector



A.2. Estimating firm size premia in the CPS ASEC

Following Song et al (2019) (and others), we estimate the firm size wage premium using the CPS-ASEC sample over 1990-2019 (the years for which the CPS-ASEC collected respondents' employer size). We restrict the sample to private sector workers. Our key independent variable is the size of workers' employer in the last year (variable *FIRMSIZE* in the IPUMS database, which indicates "the total number of persons who worked for the respondent's employer during the preceding calendar year, counting all locations where the employer operated"). We use four size classes: fewer than 100 employees, 100 to 499 employees, 500 to 999 employees, or 1000+ employees. The ASEC only collects workers' annual earnings, weeks worked last year, and usual hours worked per week last year, so we construct our dependent variable – hourly wage – from these variables (introducing measurement error if workers misremember or misreport any of these variables).

We then regress the log hourly wage on separate categorical variables for the different firm size classes, and a large set of control variables (the same controls as in the union wage premium regression, but also including union status): age, age squared, male dummy, 6 race categories, Hispanic dummy, age # male, age squared# male, married dummy, married # male, state, dummy for central city, 6 education categories, education # age, education # age squared, education # male, dummy for full-time workers, 383 occupation categories, 250 industry categories, and a dummy for union membership or coverage (where # denotes an interaction). The union membership/coverage variable is only available for one quarter of the ASEC sample each year, which makes our estimates of the firm size premium relatively noisy if we run them separately for each year (as the sample size is relatively small). So, we run our regressions over pooled 5-year periods: 1990-1994, 1995-1999, 2000-2004, 2005-2009, 2010-2014, 2015-2019.

A.3. Estimating industry wage premia in the CPS-ORG

Following Katz and Summers (1989), we estimate industry wage premia from the CPS-ORG over 1982-2019. We restrict the sample to private sector workers, which gives us between 120,000 and 150,000 observations per year (for a total of 5.3 million observations over 1982-2019). Our independent variable of interest is the industry the worker is employed in. We estimate industry wage premia in separate regressions at three different levels of industry aggregation: 18 sectors (aggregated from the CPS IPUMS *ind1990* industry variable to sectors at the NAICS level, excluding "Management of Companies and Enterprises"), 56 industries

corresponding to BEA industry codes (roughly, NAICS 3-digit industries), and 228 detailed industries, which correspond to SIC industries (at the level of the *ind1990* codes in CPS-IPUMS). More details on how we allocated workers in each *ind1990* code to each NAICS sector and BEA industry are in Appendix Section G. Our dependent variable is the log hourly wage. As in the union wage premium regressions, this is either the hourly wage reported by the worker, or the weekly earnings divided by usual hours worked at the respondent's main job (if hourly wage was not reported).[1] We then regress the log hourly wage on separate categorical variables for each industry, and a large set of control variables (the same as in the firm size regression): age, age squared, male dummy, 6 race categories, Hispanic dummy, age # male, age squared # male, married dummy, married # male, state, dummy for central city, 6 education categories, education # age, education # age squared, education # male, dummy for full-time workers, 383 occupation categories, and a dummy for union membership or coverage (where # denotes an interaction). We run the regressions separately for each year over 1984-2019, and separately for each level of industry aggregation. Note that our baseline regressions do not control for firm size, since it is only available in the CPS ASEC from 1990 onwards. However, we replicate almost identical industry wage premia estimates, controlling for firm size, in the CPS ASEC from 1990 onwards.

A.4. Estimating industry wage premia in the CPS-ORG: longitudinal estimates

Our baseline estimates of industry wage premia are estimated cross-sectionally, as described in sections I.C. and A.3. We also estimate industry wage premia in the CPS-ORG longitudinally, as a robustness check. Restricting our sample only to the individuals who can be matched from one year to the next year (using the *cpsidp* variable available at CPS IPUMS), we have between 15,000 and 45,000 unique observations in each year. The industry fixed effects in a longitudinal regression, however, are estimated only from people who move jobs from one sector to another during the 12-month period between our two observations: this means that the industry fixed effects are estimated from a sample of only 2,600-10,000 observations per year (with a median number of industry switchers of 7,803 per year). The small sample size implies that, even when estimating the industry fixed effects only for our sample of 9 large SIC sectors

[1] Note that the CPS top-codes earnings data for high-earning individuals. The (weighted) share of respondents with top-coded earnings in the private sector varies as the top-coding threshold changes three times over our sample period: the lowest share is 1% in 2000 and the highest share is to just under 5% by 2019. Excluding CPS respondents with top-coded incomes makes no perceptible difference to our estimated sector wage premia or industry wage rents.

(or 18 NAICS sectors), estimates of the industry fixed effects are rather noisy. Measurement error of industry coding, which is well-documented in the CPS (see e.g. Kambourov and Manovskii 2008**)**, may then lead to concerns of relatively serious attenuation bias. Nonetheless, we find that there is a strong and highly statistically significant relationship between the log wage fixed effects we estimate from the large cross-sectional samples, and the log wage fixed effects we estimate from the smaller longitudinal sample of industry movers. Averaging the wage effects over 5-year periods within sector, a regression of the cross-sectional wage effects on the longitudinal wage effects, weighted by industry compensation, gives a coefficient of exactly 2 (with a standard error of 0.1 and R-squared of 74%) – supporting our practice of halving the raw cross-sectional fixed effects to estimate the true industry wage premia.

Figure A2 shows estimated log wage fixed effects for each NAICS sector, relative to Retail Trade, where each point on the plot represents the average log wage fixed effect for a NAICS sector over a five year period (1982-1984, 1985-1989, 1990-1994, 1995-1999, etc.). There is an extremely close relationship between the estimated fixed effects from the cross-sectional data vs. from the longitudinal data. In addition, the decline in the standard deviation of the longitudinal industry log wage fixed effects is proportionally as large or larger than the decline in the standard deviation of the cross-sectional industry log wage fixed effects, as shown in Figure A3.

Figure A2: Correlation between cross-sectional and longitudinal industry wage fixed effects

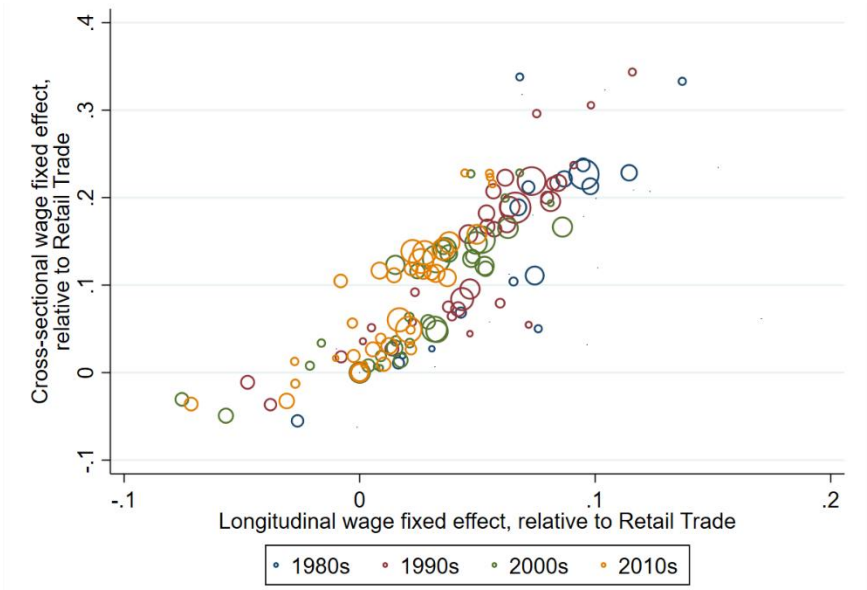
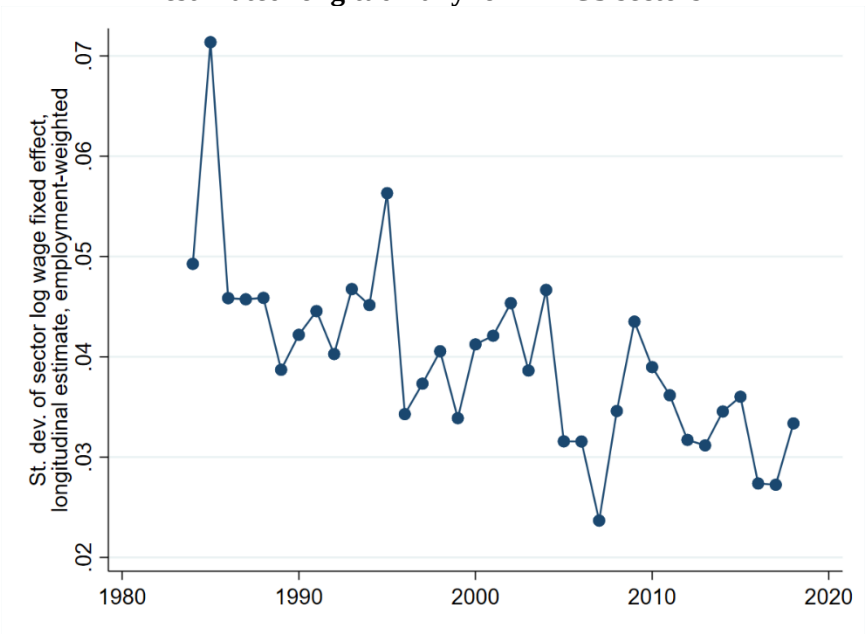


Figure A3: Employment-weighted standard deviation of industry log wage fixed effects, estimated longitudinally for NAICS sectors



A.5. Benchmarking our estimates of industry wage premia against the literature

Our estimates of industry wage premia involve (1) estimating industry log wage fixed effects cross-sectionally in the CPS across sectors, controlling for a large number of person- and job-level covariates; (2) rescaling these fixed effects relative to Retail Trade (which is set to have a wage premium of zero); and (3) cutting these estimates in half. There may be concerns, however, that our procedure of cutting the coefficients in half does too little – or too much – to account for unobserved productivity or for compensating differentials. Either unobserved productivity or compensating differentials could generate variation in industry fixed effects without rents being the underlying cause.

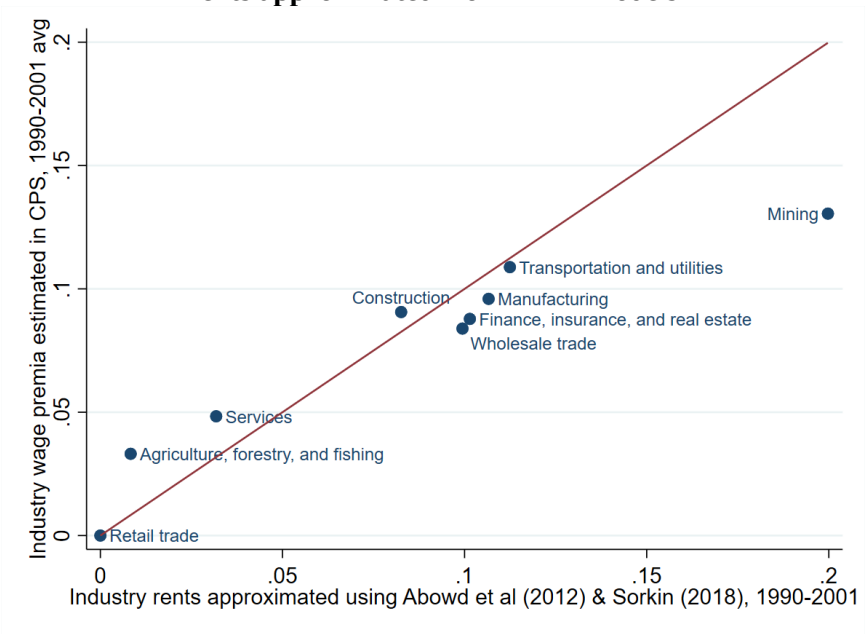
These concerns should be somewhat assuaged by the analysis in Appendix Section A4, which shows that estimates of sector wage premia from sector movers in the longitudinal component of the CPS – controlling for person-level fixed effects – are very highly correlated with our estimates from the cross-sectional CPS and are exactly half as big, on average. This gives strong support to our practice of using the cross-sectional effects and cutting them in half. *(We use the cross-sectional estimated effects, rather than the longitudinal ones, as the sample size is much larger so they are much less noisy).*

As an alternative check on our methodology of cutting the fixed effects in half to obtain wage premia, we also benchmark our estimates against estimates from Abowd et al (2012) and

Sorkin (2018), two papers which use employer-employee matched administrative data in the U.S. to study, respectively, the role of firm fixed effects in industry wage differences, and the role of rents in firm fixed effects. Abowd et al (2012) use an AKM decomposition to estimate firm and worker effects in different industries and provide data on the average firm fixed effect within each SIC 1987 industry for the period 1990-2001. Sorkin (2018) decomposes the degree to which the estimated firm fixed effects in an AKM model are due to rents versus compensating differentials and finds that around 1/3 of firm fixed effects are due to rents while 2/3 are due to compensating differentials.

We use these two papers to generate approximate estimates of industry wage premia which are due to rents, for each of the 9 SIC sectors. First, we take the Abowd et al (2012) estimates of the average firm effect across SIC industries, and aggregate these up to the level of 9 SIC sectors using a simple average. We then rescale these sector-level average firm effects relative to Retail Trade, setting the average firm effect for Retail Trade to be zero. We finally divide these estimates by three, reflecting Sorkin's (2018) finding that only 1/3 of estimated firm fixed effects reflect rents. We compare our estimates of industry wage premia due to rents, approximated using Abowd et al (2012) and Sorkin (2018), with our baseline estimates of industry wage premia estimated in the CPS over the same time period of 1990-2001. The comparison can be seen in Figure A4. For all sectors except Mining, there is a strikingly close relationship between the two estimates. That is, our estimates of industry wage premia from the CPS over 1990-2001 line up well with our back-of-the-envelope estimate of industry rents from Abowd et al (2012) and Sorkin (2018) – estimated using results from papers which explicitly remove the effects of unobserved productivity (through worker fixed effects) and compensating differentials (through the Sorkin (2018) procedure). This can give us some degree of confidence that our estimates of industry wage premia do primarily reflect rents.

Figure A4: Correlation between industry wage premia as estimated from CPS, and industry rents approximated from AKM models



A.6. Decline in the variance of industry wage premia: alternative weighting

Our estimation of the decline in the variance of industry wage premia may be sensitive to weighting choices we make, both in the estimation of the industry fixed effects in the wage regressions, and in the weighting across industries when constructing the standard deviation of the fixed effects. In our baseline scenario in section I.C. of the paper, we weight each person equally in the estimation of the industry wage fixed effects, and we weight each industry by its employment when calculating the standard deviation of the fixed effects. Here, we present three figures to show that the weighting decisions do not have a substantial impact on the estimated outcomes.

In Figure A5, we show the equal-weighted and employment-weighted standard deviations of the industry log wage effects estimated with equal weights across people. The similar trend in both equal-weighted and employment-weighted standard deviations is another way of illustrating the fact that the majority of the decline in the variance of industry wage premia occurred *within* industries. In Figure A6, we show the equal-weighted and employment-weighted standard deviations of the industry log wage effects, estimated with *log wage* weights across people in the initial regressions using the CPS data. In Figure A7, we show the equal-weighted and employment-weighted standard deviations of the industry log wage effects, but estimated with *wage* weights across people in the initial regressions. While the wage-weighted

estimates are noisier than the equal-weighted estimates, the pattern is very similar across all three figures. The industry wage premium estimates with the different weighting schemes are also very similar, as shown in Figure A8.

Figure A5: Decline in standard deviation of industry log wage effects: equal-weighted and employment-weighted

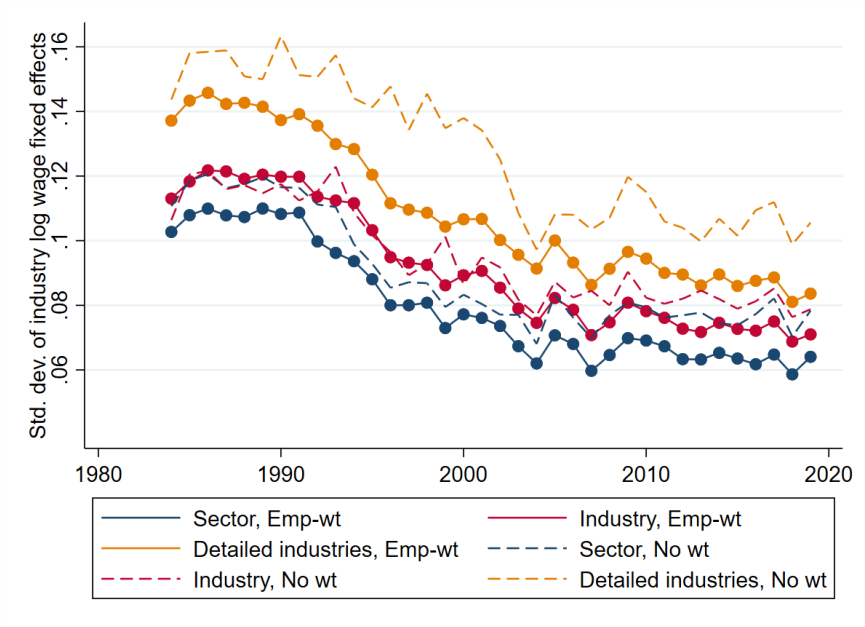


Figure A6: Decline in standard deviation of industry log wage effects, with log-wage weighting in underlying regressions

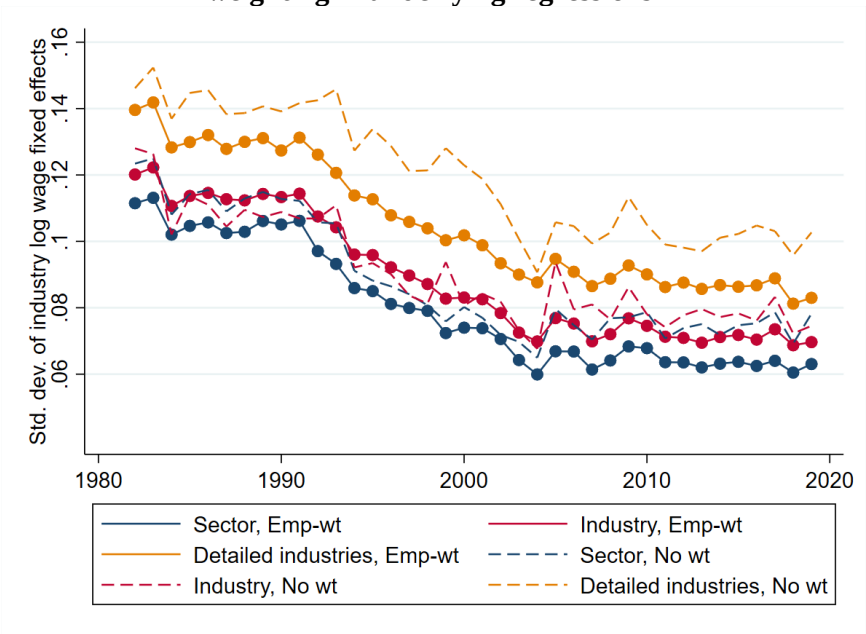


Figure A7: Decline in standard deviation of industry log wage effects, with wage weighting in underlying regressions

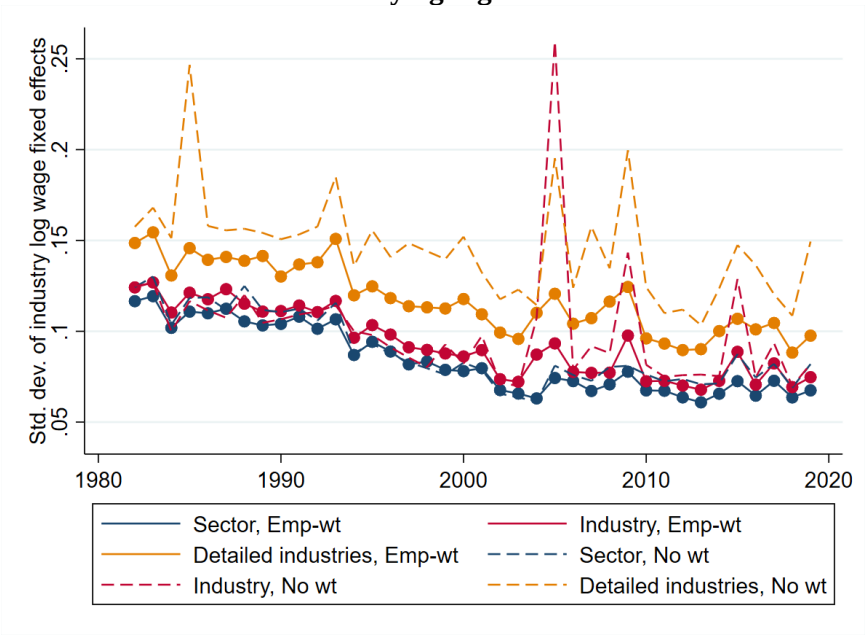


Figure A8: Comparison of estimated industry log wage premia, relative to Retail Trade (2016), estimated with equal weighting in regressions vs. wage weighting in regressions

A.7. Increasing variance of industry-level profitability

As we note in section I.C., even if we interpret industry wage premia as rents to labor, a decline in the dispersion of industry rents going to labor could be a result of (some combination) of three factors: (1) a fall in the rent-sharing coefficient holding total rents constant, meaning

total rents to labor fall, as workers at high-rent industries no longer do as well as they did before; (2) a reallocation of workers from industries with high labor rents (either because of high rent-sharing or high rents) to industries with low labor rents, which would mean that total rents to labor have fallen, but only because of structural changes in the economy; or (3) a fall in the dispersion of rents across industries, holding the rent-sharing coefficient constant, meaning total rents to labor may not have fallen. In Figures A9 and A10 below, we show that the dispersion of rents does *not* appear to have fallen across industries *(for BEA industries)*; in fact, the dispersion of profits per worker and average Q appears if anything to have risen somewhat over the period.

Figure A9: Standard deviation of industry-level measures of Q

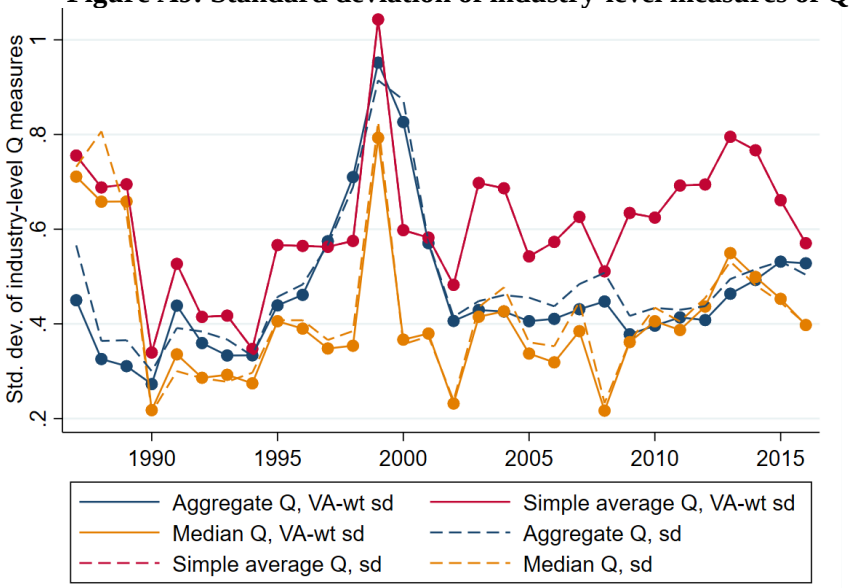
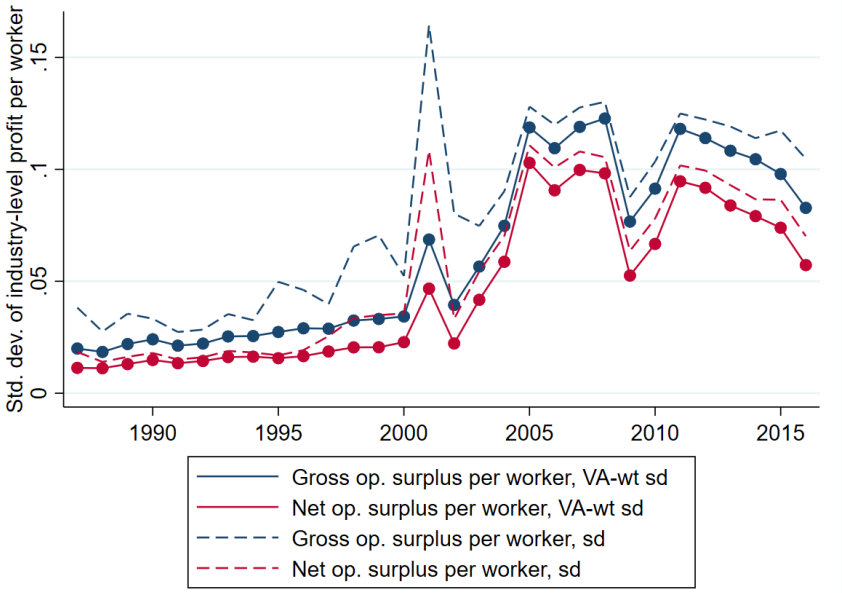


Figure A10: Standard deviation of industry-level profits per worker



Appendix B: Calculation of labor rents

B.1. Baseline: nonfinancial corporate sector

Industry rents: To create our series of sector-level wage premia, to use to calculate industry rents: For years 1984-2019, we use our estimates of sector-level wage fixed effects from the CPS-ORG as outlined in Appendix Section A3. We estimate these for SIC sectors and for NAICS sectors separately (See Appendix Section G for details as to how we crosswalk the *ind1990* industry code in the CPS IPUMS data into SIC and NAICS sectors). For years 1982-1983, we use estimates of sector-level wage fixed effects from the CPS-ORG, estimated without the union control (which is only introduced in 1984), and rescaled. Specifically, we rescale the estimated fixed effects for 1982-1983 using the ratio of the fixed effects without union controls to the fixed effects with union controls over 1984-2019 (in practice, the estimates are very similar).

We then convert these sector-level wage fixed effects into our estimated sector wage premia for each sector *S* by setting the wage premium for Retail Trade to zero, then taking half the difference between the fixed effect for sector *S* and the fixed effect for Retail Trade.

To calculate aggregate industry rents for years 1982-1986, we use BEA NIPA compensation by sector at the SIC level, along with our SIC level sector wage premium estimates. To calculate aggregate industry rents for each year from 1987 to 2016, we use BEA NIPA compensation by industry at the NAICS level, along with our NAICS level industry wage premium estimates.

For our baseline calculations for the nonfinancial corporate sector, we exclude the SIC sector "Finance, insurance, and real estate" (for 1982-1986) and we exclude the NAICS sectors "Finance and insurance" and "Real estate, rental, and leasing" (for 1987-2016). We also estimate industry rents for SIC industries for 1987 to 1997 to understand the degree to which the SIC-based and NAICS-based series are comparable. The series move almost identically together, but the SIC series is slightly higher than the NAICS series. To adjust for this, we take the average ratio of the NAICS labor rents series to the SIC labor rents series over 1987-1997, and scale the SIC series down by this ratio for the years 1982 to 1987.

We have the further issue that our BEA compensation by industry data is for the entire private sector, not just the corporate sector. We therefore then take our estimate of total industry

rents and scale it down by the ratio of total compensation in all private industries (excluding finance, insurance, and real estate) to total compensation in the nonfinancial corporate sector.

Union rents: We estimate the union coverage rate for all private sector workers in the CPS-ORG for years 1984-2019, excluding those in Finance, Insurance, or Real Estate. We extend this backwards to 1982 by applying the annual rate of change in the union coverage rate for all private sector workers (from unionstats.com) for 1982-83 and 1983-84. We estimate our own union wage premia from the CPS-ORG for years 1984-2019, as outlined in Appendix Section A.1. We then use the Blanchflower and Bryson (2004) series of union wage premia for the years 1982 and 1983. As shown in Figure A1, the series are very similar for the years that they overlap, and we use very similar controls to estimate the series, suggesting that this imputation is legitimate. We estimate total union rents for the nonfinancial corporate sector using the estimated union wage premia, estimates of the union coverage rate for nonfinancial private sector workers, and compensation for the nonfinancial corporate sector from the BEA NIPA.

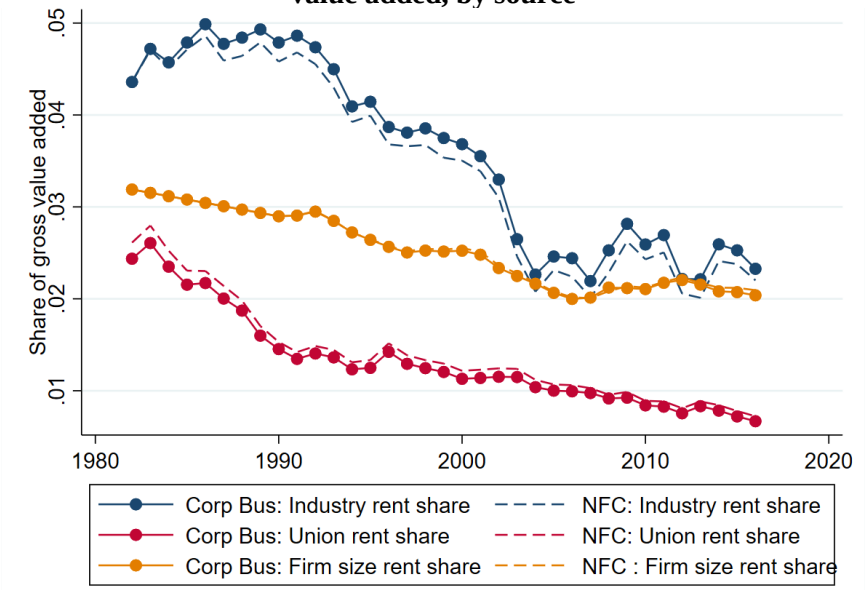
Firm size rents: We estimate firm size premia from the CPS ASEC for years 1990-2019, as outlined in Appendix Section A.2. We use the Census Bureau's SUSB data set to calculate the total payroll share by firm size category in each year, for three categories: less than 100, 100-499, and 500+ workers. We then apply these payroll shares to total compensation for the nonfinancial corporate sector in each year, from the BEA NIPA, to obtain estimated shares of compensation in each firm size category. We estimate total firm size rents for the nonfinancial corporate sector for 1990-2019 using our firm size premia and these estimated compensation shares. To calculate firm size rents for the years 1982-1989, we refer to Levine et al (2002) who show estimates of the distribution of employment by firm size in 1979 and 1993 (their Table 4.1), and the estimated firm size log wage effect in 1979 and 1993 (their Table 4.3), for firms of 100-999 workers and 1,000+ workers. We estimate the change in firm size rent share over 1979-1993 which would be implied by their estimates, which is around 0.4 percentage points. We then note that in our data, the firm size rent share does not change much between 1990 and 1993. We therefore use the estimated decline in the firm size rent share of 0.4 percentage points to impute total firm size rents in 1979 to be equal to total firm size rents in 1990 + 0.4 percentage points. We linearly interpolate the firm size rents in each intervening year 1980-1989.

B.2. Alternative calculation: corporate sector

Our baseline estimates in Section II (and described above in Appendix Section B.1.) are for the nonfinancial corporate sector. Here we replicate our calculation for total labor rents, but for the entirety of the corporate sector: that is, the calculation includes the finance industry. We do not find a substantially different pattern for the corporate sector relative to the nonfinancial corporate sector, as shown in Figure B1. Figure B2 breaks out the differences in the series by source, showing that union rents are slightly higher as a share of nonfinancial corporate value added as compared to corporate value added, but industry rents slightly lower.

Figure B1: Labor rents as share of corporate business value added

Figure B2: Labor rents as share of corporate and nonfinancial corporate business ("NFC") value added, by source



Differences between the corporate sector and nonfinancial corporate sector estimates of labor rents are as follows:

1. **Union rents:** The nonfinancial corporate sector series uses our estimate of the unionization rate excluding finance, insurance, and real estate. The corporate sector series uses the unionization rate across all private industries. Because unionization in finance, insurance, and real estate is lower than average, this means that union rents as a share of value added in the corporate sector is slightly lower than union rents as a share of value added in the nonfinancial corporate sector.
2. **Industry rents:** Our estimate of industry rents for the nonfinancial corporate sector excludes any rents in finance, insurance, or real estate. Our estimate of industry rents for the corporate sector includes labor rents in finance, insurance, and real estate (though the magnitude of estimated industry rents in real estate is too small to affect the overall calculation much). There are three forces operating on our series for industry rents in the corporate sector: (1) industry rents in finance were lower than the average industry rents outside of finance for our whole sample period, acting to make the level of total industry rents as a share of value added lower for the corporate sector as a whole than for the nonfinancial corporate sector; (2) the share of finance in value added and compensation grew from the 1980s to the 2010s; and (3) industry rents fell much more slowly in the financial sector than in non-financial sectors, which would operate to make the decline in overall industry rents as a share of value added less steep for the corporate sector than the nonfinancial corporate sector.[2]
3. **Firm size rents:** Firm size rents as a share of value added is by definition the same in both sectors, as we use the same methodology for both sectors (see Appendix Section B.1.).

Top-coding and high earners in the financial sector: One major caveat to these estimates of labor rents in the nonfinancial corporate sector is that – since the CPS earnings data is top-coded

[2] Industry rents in finance – as we estimate them from the CPS – fell very gradually in the 1980s and 1990s, and then levelled off at around 1.5% of financial sector value added in the 2000s. Industry rents in non-financial sectors fell much more sharply in the 1980s and 1990s, and then levelled off at around 2% of nonfinancial sector value added in the 2000s. Over the same period, the financial sector grew as a share of both compensation and value added: in the BEA NIPA Industry Accounts data, the share of total compensation (in private industries) in finance, insurance, and real estate rose from around 9% in the late 1980s to around 11% by the 2010s.

(e.g. at $2,885 per week for the 2000s and 2010s) – we will not pick up the very large increases in compensation for the highest earning financial sector workers over the period, which may well reflect rents (see, e.g. Phillipon and Reshef 2006). This means that our series of industry rents should be thought of – as discussed in Section II – as a series measuring industry rents that flow to the *majority* of workers.

Because the top-coding thresholds jump, the share of CPS respondents who are top-coded varies over time. In our CPS-ORG data, the (weighted) share of workers in Finance, Insurance, and Real Estate who had top-coded earnings rose from 2% in 2000 to 9% by 2019. (The share in the overall data for private sector rises from 1% in 2000 to just under 5% by 2019). If the finance wage premium for high-earning financial professionals is growing over time over the 2000s and 2010s even as it slightly declines for the majority of finance sector workers – which seems possible – then our estimates of labor rents *overestimate* the decline in labor rents going to all workers, but are a good estimate of labor rents going to *the majority* of workers.

A quick counterfactual estimate, however, suggests that the degree to which the exclusion of top-earning workers in finance might affect our calculations is relatively limited. Assume for example that a rise in rents going to top earners drastically changed the average wage premium in Finance and Insurance, meaning that it rose from 11% to 15% over 1987-2016, rather than falling from 11% to 8%. In this case, our estimate of total industry rents as a share of value added in the corporate sector would have fallen from 3.9% to 2.3%, rather than from 3.9% to 2.0%. over 1987-2016.

B.3. Labor rents for college and non-college workers

In Section II.D. we estimate labor rents for college and non-college workers separately. Our estimates go from 1984-2016 (rather than 1982-2016 for the aggregate calculation) because we are only able to obtain estimates of union wage premia and unionization rates by education group for 1984 onwards. We estimate that labor rents to non-college workers, as a share of net value added in the nonfinancial corporate sector, fell substantially over 1987-2016, while labor rents to college workers rose slightly. This, however, is the result of two effects: a compositional effect as the share of the labor force without a college education fell over this period, and a within-group effect as labor rents fell by more for college workers than for non-college workers (Figure B4).

Industry rents: For industry rents, we estimate sector wage premia in the CPS separately for workers with a four year college degree and for workers without a four year college degree. We also use the CPS to estimate the total share of earnings by education group within each sector in each year. Using these earnings shares and the BEA NIPA Industry Economic Accounts, we estimate total compensation by education group and sector, and apply our sector-by-education-by-year wage premia.

Union rents: We estimate union wage premia and union coverage rates in the CPS separately for workers with a four year college degree and for workers without a four year college degree. We also use the CPS to estimate the total share of earnings by education group in each year. We use these, and total compensation for the nonfinancial corporate sector from the BEA NIPA, to estimate total union rents for college and non-college workers for each year.

Firm size rents: We estimate firm size wage premia in the CPS separately for workers with a four year college degree and for workers without a four year college degree. We also use the CPS to estimate the total share of earnings by education group and firm size class in each year. We use these, the payroll shares by firm size class from the Census Bureau SUSB, and the total compensation for the nonfinancial corporate sector from the BEA NIPA, to estimate total firm size rents for college and non-college workers for each year from 1990 onwards. We are unable to calculate our own estimates of firm size rents for years pre-1990. However, our estimates of firm size rents as a share of total compensation for each education group, for the years 1990-2019, show very consistent and strongly divergent trends, so we interpolate these same trends backwards through 1984 (as shown in Figure B5) and use these trends to impute firm size rents for years 1984-1989. This imputation is consistent with our imputation of firm size rents at the aggregate level using data from Levine et al (2002), as described in Appendix Section B.1. (in terms of the change in total firm size rents as a share of value added).

Figure B3: Estimated labor rents as share of net value added, nonfinancial corporate sector, by education group (3-year moving average)

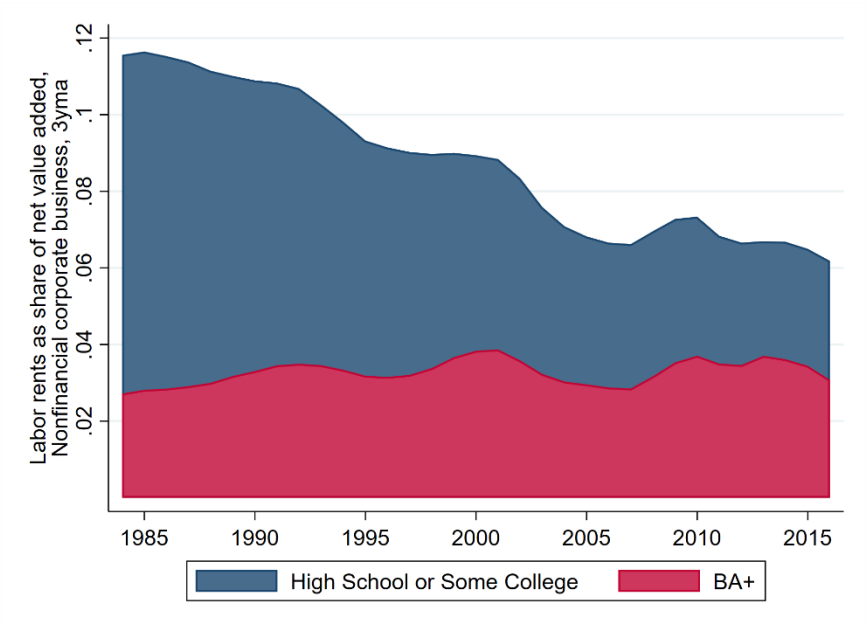


Figure B4: Estimated labor rents as share of compensation, by education group (non-financial corporate sector)

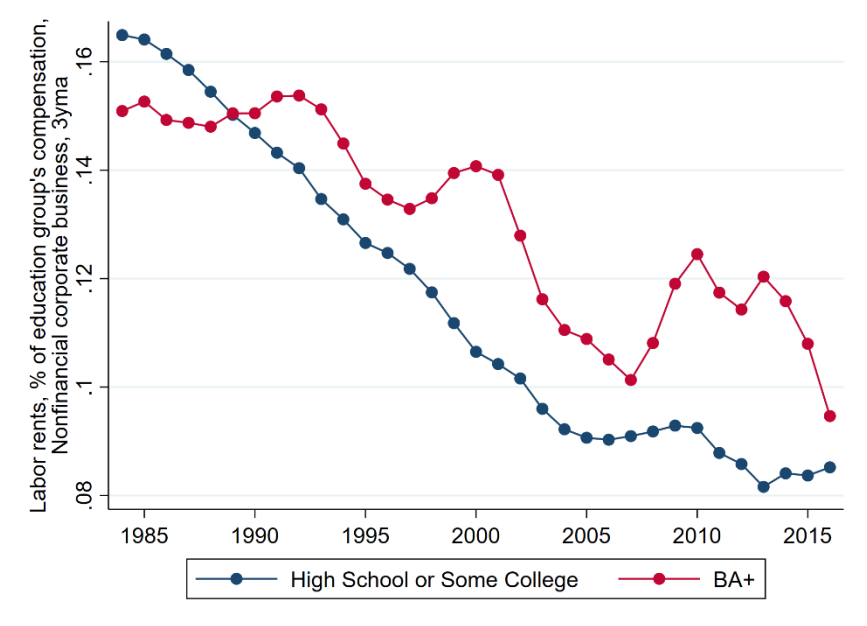
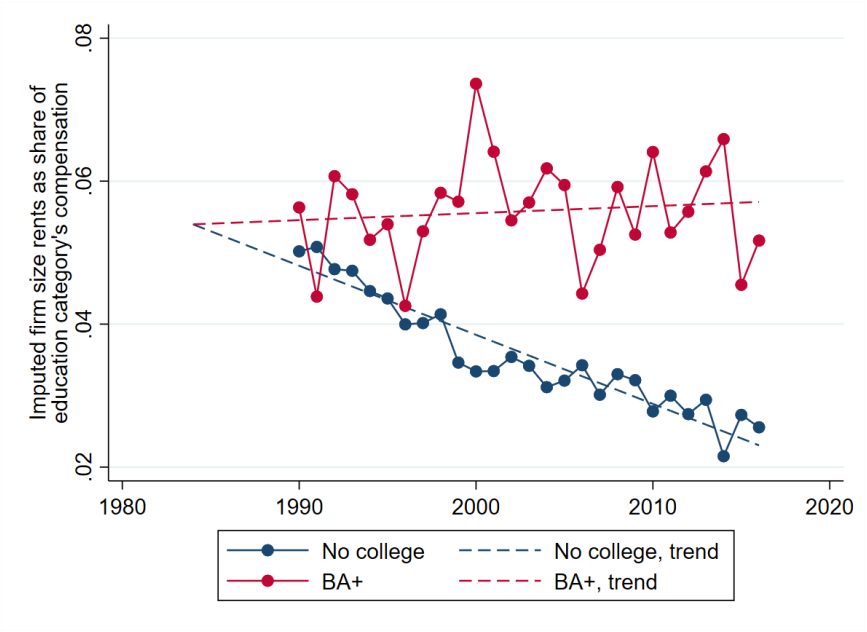


Figure B5: Firm size rents as a share of compensation, by education group: estimates and trend



B.4. State-level labor rents calculations

We estimate state-level labor shares using the Regional Economic Accounts from the Bureau of Economic Analysis. We use the state-level estimates of GDP and compensation for all Private Industries to calculate the labor share (compensation/GDP).

To calculate our labor rents measure at the state level, we first use the CPS-ORG data to estimate industry-by-state, firm size-by-state, and union-by-state wage premia for each year 1984-2019, using the full set of controls described in Appendix sections A.1.-A.3.

Industry rents: We estimate industry wage premia by state at both the NAICS sector level and the SIC sector level, using the crosswalk from Census industry codes to NAICS and SIC sectors described in Appendix Section G. We obtain state-level compensation at the industry level from the BEA Regional Economic Accounts data, which provides data on NAICS industries for 1997 onwards and for SIC industries for years up to and including 1997. We calculate industry rents with the formula in Section II of the paper, using NAICS compensation by industry and the industry wage premia estimated using NAICS codes for 1997-2017, and SIC compensation by industry and the industry wage premia estimated using SIC codes for 1984-1996. We then take the ratio of estimated industry rents at the state level using NAICS industries,

relative to the estimated industry rents using SIC industries, in 1997, and apply this backwards over 1984-1996 to create a roughly consistent series over time.[3]

Union rents: We estimate the union coverage rate by state from the CPS, and calculate union rents using the state-level union coverage rate and union wage premium.

Firm size rents: We estimate the firm size wage premium by state from the CPS ASEC for years 1990-2019, use data on the distribution of payroll by firm size and state from the Census Bureau SUSB database to estimate payroll share by firm size class, and then apply this to compensation by state from the BEA Regional Economic Accounts to estimate firm size rents by state for each year from 1990-2016. To estimate firm size rents from 1984-1989, we use the data from Levine et al (2002), whose data suggests that firm size rents fell by 0.4% of value added from 1979 to 1993 at the national level. As in our national level estimates, we therefore apply a fall of 0.4% of state-level GDP to our firm size rents calculations for each state over 1979-1993, with a linear interpolation for each year between these dates.

B.5. Industry-level labor rents calculations

Our calculation of industry rents largely follows the methodology for the aggregate level outlined in Section B.1, with the notable exception that we do not calculate firm size rents as we do not have payroll data by firm size at the industry level.

Industry rents: We estimate industry wage fixed effects by state at the level of 51 industries (BEA industry code ~ NAICS 3-digit level), over 1987-2016, in the CPS-ORG. We then calculate the industry wage premium as half of the difference between the estimated fixed effect for each industry, relative to the lowest-wage large industry, which is Food Services and Drinking Places. This industry had 12.3 million employees as of February 2020, and average hourly earnings of $15.25 as of October 2019 (the latest data available from the BLS at time of writing). We obtain industry-level compensation at the NAICS 3-digit level from the BEA Industry Economic Accounts, and aggregate this to the BEA industry code level.

Union rents: We use our estimates of the union wage premium at the national level, and estimate the union coverage rate by industry using the CPS. Our results are not sensitive to

[3] The state level calculations use all private industries' GDP and compensation as their baseline as we do not have state-level data on the nonfinancial corporate sector only. As such, we include industry rents for financial industries in this calculation.

estimating the union wage premium separately for each individual industry, rather than using the aggregate union wage premium.

Firm size rents: We do not include firm size rents in our measure of total labor rents by industry, because we do not have data on compensation by firm size class and 3-digit NAICS industry.

B.6. Were labor rents redistributed or destroyed? Cross-industry analysis

In Section II.E., we address the question: were labor rents redistributed or destroyed? We predict that, if the decline of labor rents is because rents in specific industries were destroyed as a result of globalization or increased competition, then one would expect (1) that returns to capital would fall alongside rents to labor, and (2) that the total rents in the industry – profits, plus labor rents – would be falling.

We look at 51 industries over 1987-2016 to establish whether this was the case (industries at the BEA industry code/roughly NAICS 3-digit level, as in the industry-level analysis in Sections III and IV of our paper).

We measure three items to answer these questions:

1. **The profit rate to capital**, which we measure as net operating surplus minus a rough measure of the cost of capital,[4] over fixed assets;
2. **The rent rate to labor,** for which we use our measure of labor rents, divided by fixed assets; and
3. **The total rent rate,** which is the sum of the profit rate to capital and the rent rate to labor.

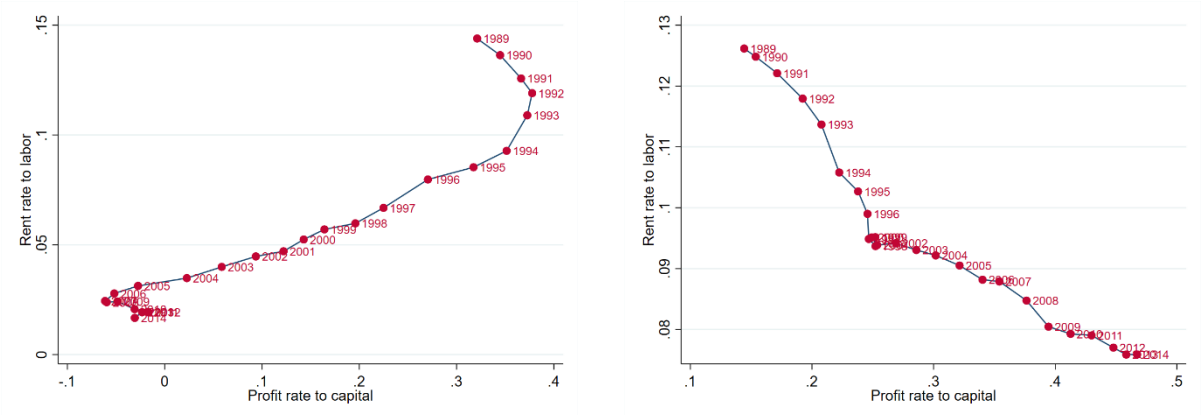
We calculate these three statistics for each of the 51 industries under consideration and compare their average values in 1987-91 and 2012-16, the start and end of our sample period.[5]

The industries of apparel manufacturing and wholesale trade give particularly striking examples of our heuristic to distinguish between rent destruction vs. rent redistribution, shown in Figure B5. In apparel manufacturing, the profit rate to capital and rent rate to labor both fell very substantially over 1987-2016 *(the figure shows 5-year centered moving averages)*. This suggests that in apparel manufacturing, the dominant trend was a destruction of rents – as would accord

[4] We use the 3-month Treasury rate, plus a 5% fixed equity premium, minus a backward-looking measure of inflation expectations (a 3-2-1 weighted average of PCE inflation over the previous three years). This does not account for differential costs of capital in different industries, perhaps caused by differential risk across industries.
[5] This is the longest sample period for which we have industry-level data for consistently defined NAICS-based industry codes.

with the substantial rise in low-wage import penetration over the period. On the other hand in wholesale trade, the decline in the rent rate to labor was more than matched by an increase in the profit rate to capital over the period, suggesting that the dominant trend was a redistribution of rents from labor to capital.

Figure B5: Imputed profit rate to capital and rent rate to labor, Apparel manufacturing (left) and Wholesale trade (right)



We can analyze this more systematically by categorizing industries into groups based on the changes in the profit rate to capital and rent rate to labor over the period, as shown in Table B1. For each category, we show the number of industries in this category and the share of the private sector workforce in 2018 which was employed in these industries (which we calculate using the BEA NIPA employment by industry database).[6]

We find that in 29 industries, employing around 30% of the private sector workforce, the profit rate to capital rose even while the rent rate to labor fell over 1987-2016. Together, these 29 industries were responsible for 73% of the total decline in labor rents over the period. Further, in the majority of these industries – 21 industries, employing around 24% of the private workforce – returns to capital rose *by more than* rents to labor fell over 1987-2016, implying that the total underlying profits generated by these industries rose, even as rents to labor fell (i.e., the total rent rate rose). These industries – those where the increase in profits to capital was greater than the decline in rents to labor – were responsible for 38% of the total decline in labor rents over 1987-2016. These calculations suggest a substantial role for redistribution in the decline in labor rents.

[6] Note that the totals do not add up to 100%, because this industry-level analysis excludes financial industries to be consistent with our main analysis in the paper.

Table B1: Industries, categorized by changes in profit rate to capital and rent rate to labor, 1987-2016

	Profit rate to capital rose	**Profit rate to capital roughly the same**[7]	**Profit rate to capital fell**
Rent rate to labor rose	1 industries <1% of private sector workforce	0 industries	0 industries
Rent rate to labor roughly the same[118]	5 industries 13% of private sector workforce	0 industries	0 industries
Rent rate to labor fell	29 industries 29% of private sector workforce	2 industries 18% of private sector workforce	14 industries 30% of private sector workforce

Figures B6, B7, and B8 break down these statistics at the industry level, showing the profit rate to capital and rent rate to labor in each of 1987-91 and 2012-16.

Figure B6, showing manufacturing industries, shows that for the majority of manufacturing industries the total rent rate changed very little over the period, but the distribution of those rents changed substantially as rents were redistributed from labor to capital – see, for example, the cases of autos and transportation equipment (*Dur_transp*), plastics (*Nondur_plastic*), fabricated metal products (*Dur_fab_metal*), chemical products (*Nondur_chemical*), paper products (*Nondur_paper*), or printing (*Nondur_printing*). In some industries, total rents were destroyed, with both labor and capital seeing rent destruction: apparel and furniture manufacturing (*Nondur_apparel* and *Dur_furniture*) being the most prominent cases (and two of the most exposed to low-wage import competition over the period). A handful of sectors actually saw total rents rise substantially even as labor rents fell, in particular food, beverage and tobacco products (*Nondur_food*) and petroleum products (*Nondur_petro*).

Figure B7 shows the same statistics for Trade, Transportation, Construction, and Utilities industries. Here, the picture is more mixed (and note the different scale on the axis, relative to the manufacturing graph). Retail trade, trucking, and construction (*Retail_trade*, *Transp_truck*, *Construction*) saw relatively large decreases in their total rent rate over this period, but this decrease appeared to have been entirely borne by labor, with little decrease in the profit rate to capital (and even an increase in the profit rate to capital in the case of trucking). Mining

[7] We define "roughly the same" as being within 0.5 percentage points of its 1987-91 level in 2012-16.

industries (*Min_oil_and_gas*, *Min_ex_oil*), and passenger transportation (*Transp_passenger*) saw large increases in their profit rate without an increase in the rent rate to labor. Wholesale trade saw a large increase in its total rent rate *even as* the rent rate to labor substantially decreased.

Finally, Figure B8 breaks down the trends for service sector industries. It excludes financial and legal services, since their very low fixed assets means their ratios are off the scale on the graph. Particularly notable here are the substantial declines in the labor rent rates in administrative and support services (*Adm_support*), publishing (*Inf_publishing*), and data processing (*Inf_data)* – which came alongside large decreases in the total rent rate and the profit rate to capital. One industry bucking the trend is computer services (*Computer_serv)*, which saw a large increase in the rent rate to labor over the period.

In Figure B9, we show the breakdown of the share of the total decline in labor rents accounted for by each industry. The majority of the decline in labor rents can be accounted for by industries in manufacturing, retail and wholesale trade, construction, utilities, and transportation industries.

Figure B6: Manufacturing industries – profit rate to capital and rent rate to labor, 1987-91 and 2012-2016

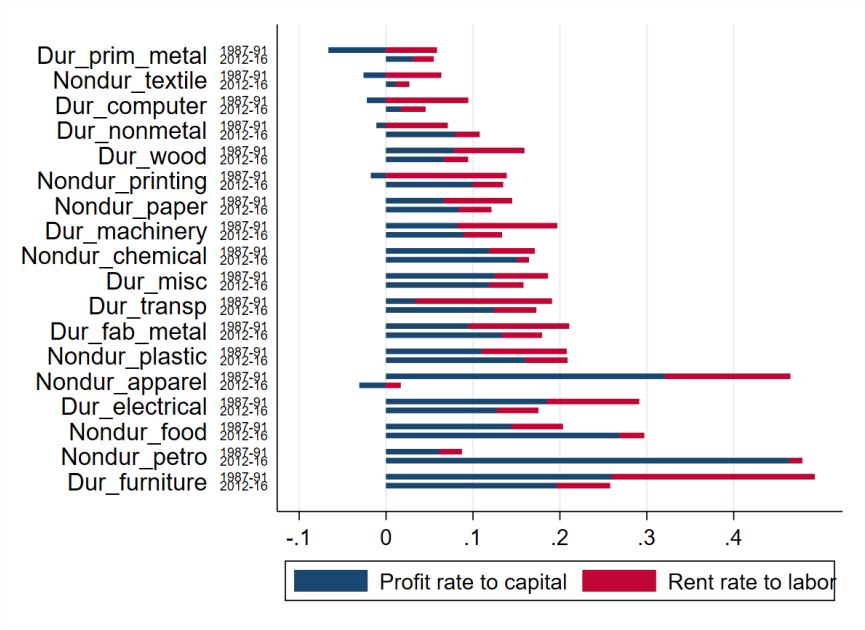


Figure B7: Trade, transportation, construction, and utilities – profit rate to capital and rent rate to labor, 1987-91 and 2012-2016

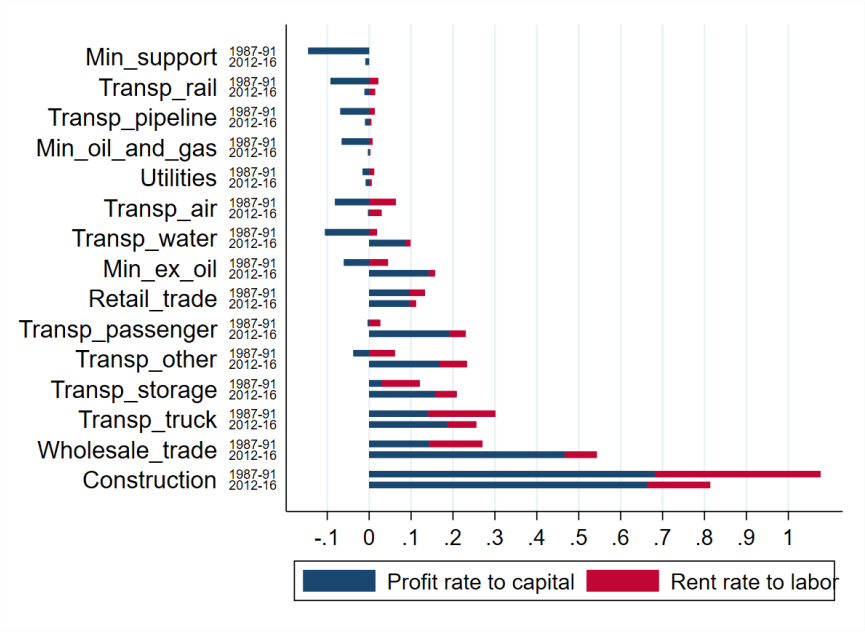


Figure B8: Services– profit rate to capital and rent rate to labor, 1987-91 and 2012-2016

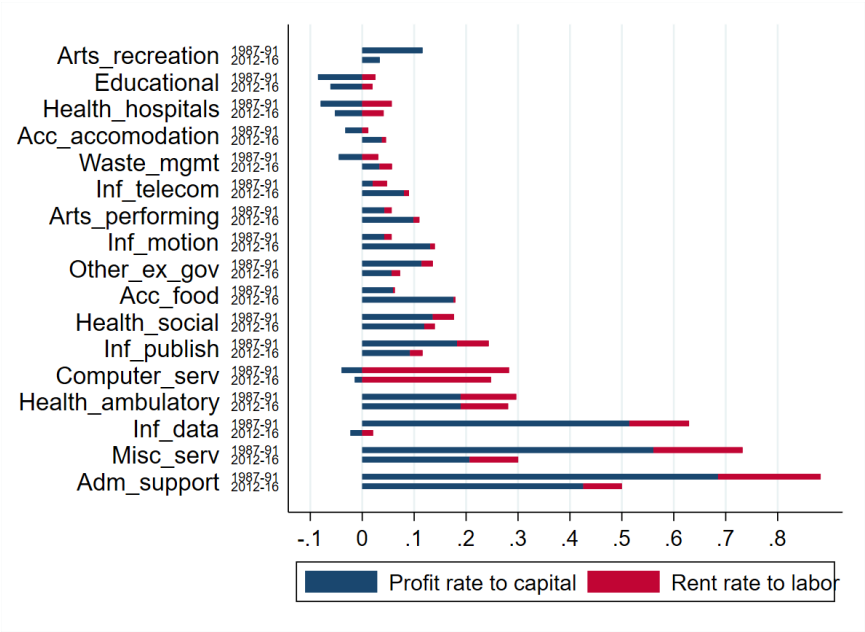
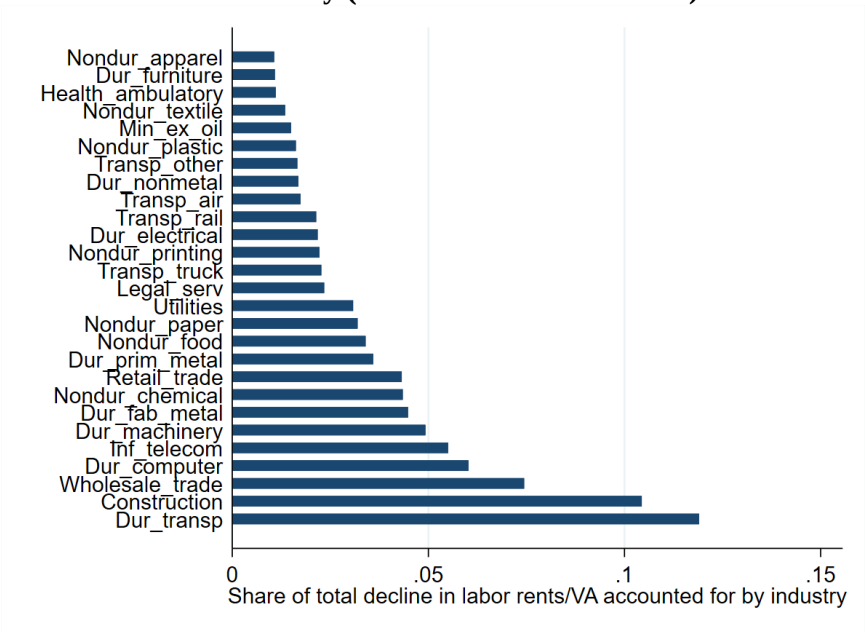


Figure B9: Share of total decline in labor rents as a share of value added, accounted for by each industry (over 1987-91 to 2012-2016)



This graph only shows industries responsible for 1% or more of the total decline in labor rents

B.7. Manufacturing industries, rents, and low-wage import penetration

In Section II.E., we show that manufacturing industries with bigger increases in low-wage import penetration over 1989-2007 *were not* the industries with the biggest drops in labor rents over the period, which would tend to cast doubt on the idea that globalization was primarily responsible for the decline in labor rents over this period. Our data on import penetration from low-wage countries over 1989-2007 is from Bernard, Jensen, and Schott (2006), updated by Peter Schott in 2011 and available on his website. Low-wage import penetration is calculated as the share of domestic sales within each industry represented by imports from low-wage countries, defined as countries with GDP per capita less than 5% of the U.S. level. We study 1989-2007 as this is the period for which we have consistently-defined data on low-wage import penetration. The data is at the NAICS 3-digit industry level, which corresponds to our 18 industry definitions in manufacturing.) with changes in profitability and the log industry wage premium, for 18 manufacturing industries

We report some additional correlations in the data here. First, as one would expect, the industries which saw bigger increases in import competition saw the biggest declines in the profit rate to capital (Fig. B10). Why, then, were they not the industries that saw the biggest declines in rents to labor? The answer is that the industries which saw the biggest rises in low-wage import

penetration over 1989-2007 were industries which for the most part already had relatively low labor rents in the late 1980s (Figure B11). Industries with high initial labor rent shares had more labor rents to lose over the 1989-2007 period, as shown in Figure B12 (though, as a percent of total labor rents, almost all manufacturing industries lost a relatively similar share: about 30%-50% of their labor rents over the period, as shown in Figure B13). Note, however, that even when controlling for the initial level of labor rents in 1989, there is still no significant relationship between the increase in low-wage import penetration and the change in labor rents over 1989-2007 (and the coefficient is in fact positive).

Figure B10: Profit rate to capital and import penetration, manufacturing, 1989-2007

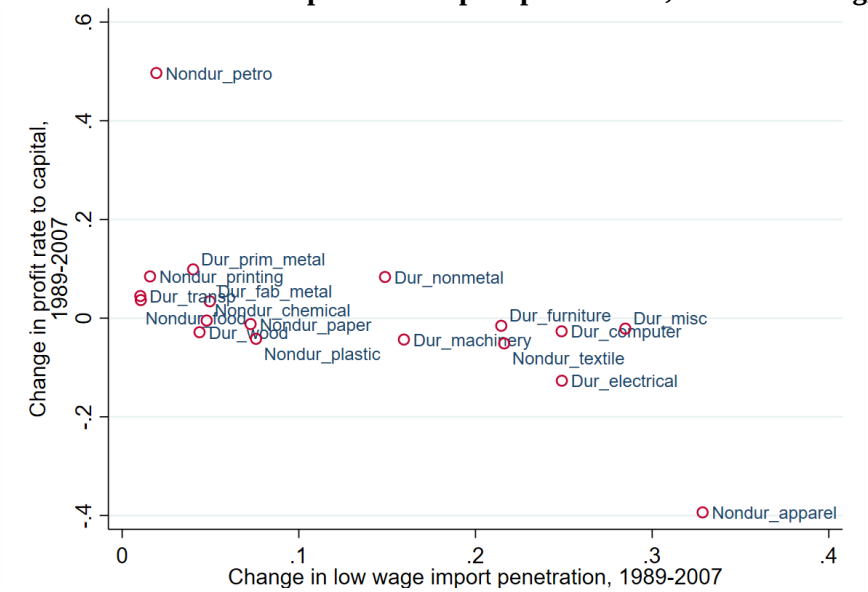


Figure B11: Initial rent share and change in import penetration, manufacturing, 1989-2007

Figure B12: Initial industry labor rent share and change in labor rent share, manufacturing, 1989-2007

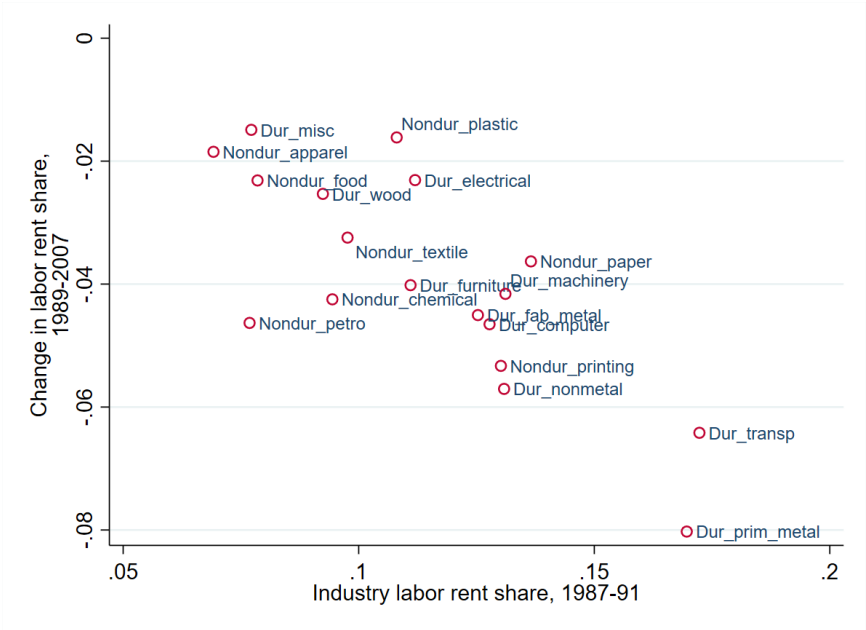
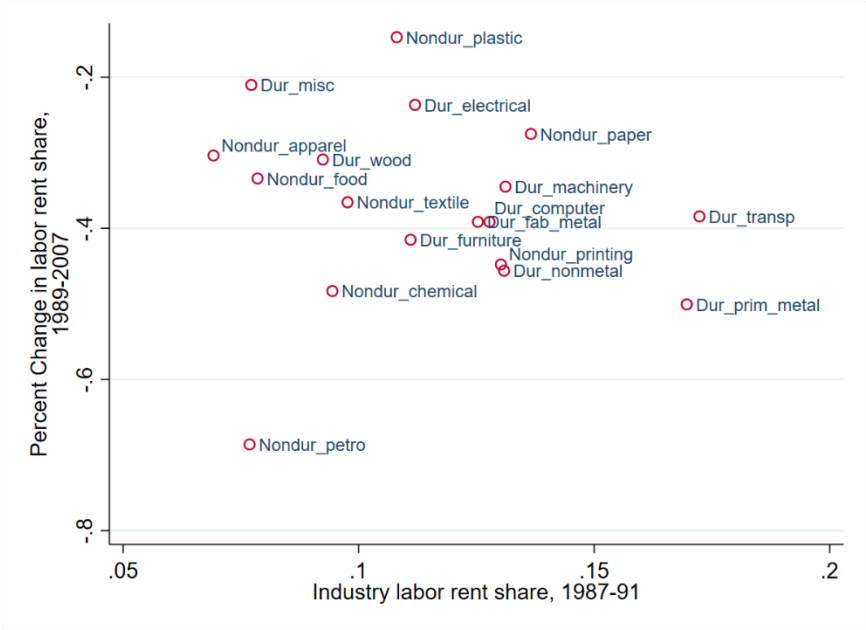


Figure B13: Initial industry labor rent share and percentage change in labor rent share, manufacturing, 1989-2007



Appendix C: Additional figures and tables

C.1. Decline in unionization by sector

We calculate unionization rates by SIC (1987) major sector in the CPS-ORG for each year from 1984 to 2019 inclusive. We show the raw declines in unionization by sector in Figure C1. Indexing the unionization rate in 1984-86 to 100, we show the 3-year moving average of the unionization rate over 1984-2019 in Figure C2. As can be seen, the proportional rate of decline in unionization was strikingly similar across almost all sectors – Mining, Manufacturing, Transportation and Utilities, Retail Trade, Wholesale Trade, and Construction – particularly until the mid-2000s. Note also that of the three sectors whose unionization rate did not decline as much – Agriculture, FIRE, and Services – Agriculture and FIRE had started with such low initial unionization levels that it would have been difficult to decline much further. Within Services, the arrest of the decline in unionization rates since 2000 was – compositionally – a result of slow decline in unionization in health, offset by an increase in unionization in education.

Figure C1: Decline in unionization rates by sector, 1984-2019 (3-year moving average)

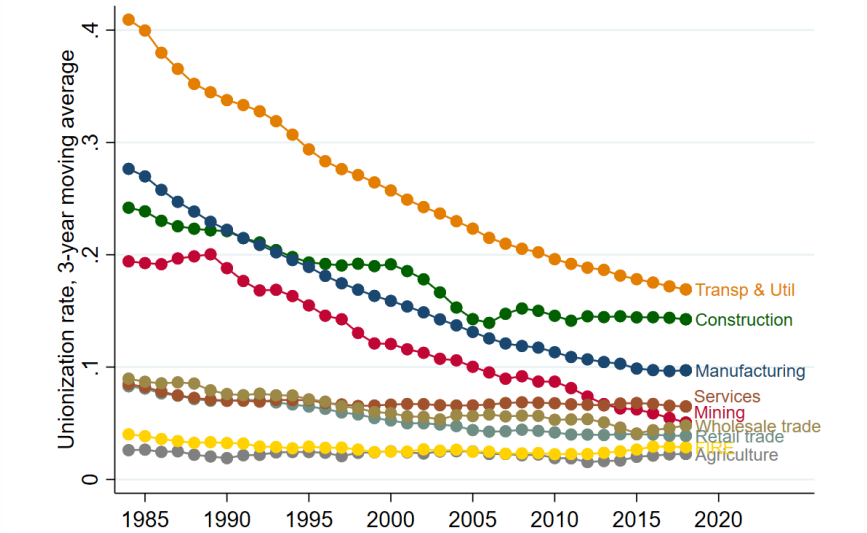
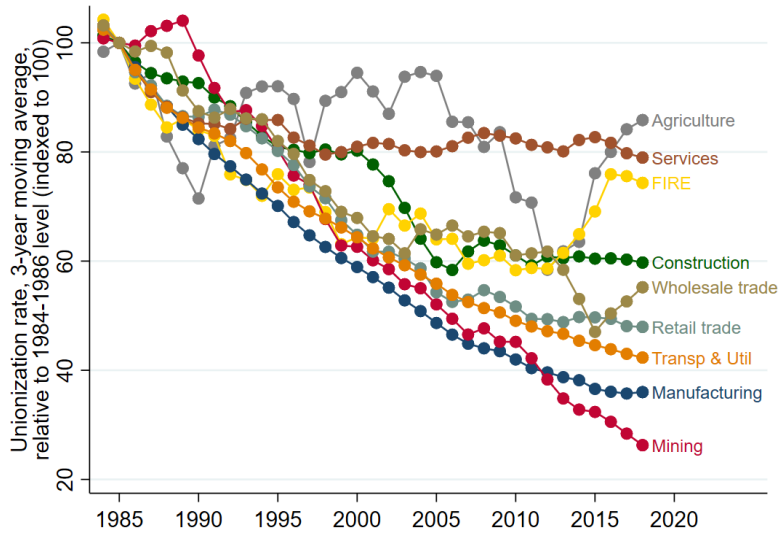


Figure C2: Decline in unionization rates by sector, 1984-2019 (3y ma, indexed to 1984-86)

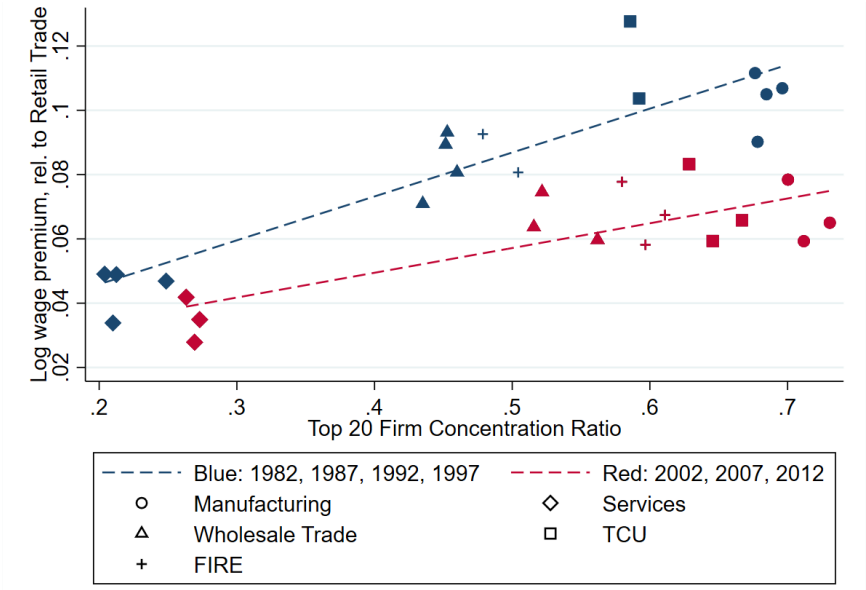


C.2. Relationship between wage premia and concentration

Figure C3 shows the correlation, at the SIC sector level, between average top 20 sales concentration and our estimated log wage premium, for 5-year periods over 1982 to 2012. As the dashed lines of best fit suggest, workers in more concentrated sectors receive higher wage premia on average, but this relationship appears to have weakened. The sector wage premium is calculated as half of the sector log wage fixed effect which we estimate from the CPS-ORG as detailed in Section I.C. Average concentration in the sector is defined as the (sales-weighted) average Top 20 Sales Concentration Ratio across SIC industries within each sector, 5-yearly from 1982 to 2012. The concentration data is calculated by Autor et al (2020) from Census data; we obtain it from their Figure 4 using WebPlotDigitizer (Rohatgi 2019). A similar relationship holds if we use the top 4 firm concentration ratio rather than the top 20 firm concentration ratio.

In regressions of concentration on wage premia at the level of our BEA industries (roughly NAICS 3-digit), we find smaller coefficients on concentration in the later period, but the difference is not statistically significant. (We use data on concentration from Covarrubias, Gutiérrez, and Philippon (2019), calculated from Compustat data for 1982-2016 and from Census data for 1997, 2002, 2007, and 2012.) Running a similar regression for the NBER CES manufacturing industries (NAICS 6-digit level) over 1997-2012 – regressing the level of top 20 sales concentration (import adjusted) on log average compensation per worker – we find that the coefficient also falls, but the change is once again not statistically significant.

Figure C3: Sector-level relationship between concentration and wage premium

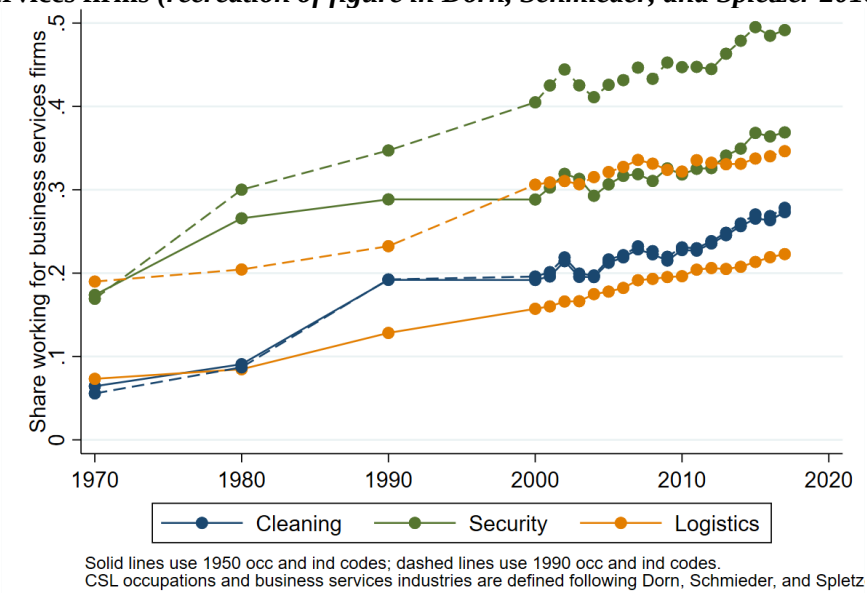


Notes: Each point is the sector average log wage premium relative to Retail Trade, calculated from the CPS-ORG, plotted against the average top 20 sales concentration ratio in the sub-industries of each major sector, calculated from Economic Census data by Autor et al (2019).

C.3. Quantifying the rise in outsourcing of cleaning, security, and logistics work

In Figure C4, we recreate Dorn, Schmieder, and Spletzer's (2018) estimates of the share of workers in cleaning, security, and logistics occupations who were working in the business services sector (indicating having had their work outsourced). Dorn, Schmieder, and Spletzer (2018) identify occupation and industry codes in the Census data which indicate outsourcing to business services, according to both the 1950 and the 1990 occupation and industry codes. Note that the series have different levels as they are calculated using 1950 and 1990 industry and occupation codes, but that the time series trend in both is similar.

Figure C4: Share of workers in cleaning, security, and logistics working for business services firms *(recreation of figure in Dorn, Schmieder, and Spletzer 2018)*



C.4. Allocation of workers to high-rent industries

If labor rents have declined, a natural question is whether workers are no longer working in the industries which produce rents. One way to visualize this is to show the share of workers working in industries with different degrees of profitability. Figure C5 shows the share of workers in industries with different levels of *median* Tobin's Q (as measured by Covarrubias et al 2019 for publicly-listed companies): there is a noticeable rightward shift, as the median Tobin's Q across industries has increased over the period.[8] Figure C6 shows the share of workers in industries with different values of gross operating surplus over fixed assets: this shows a slight downward shift, as gross operating surplus / fixed assets was lower in many industries over 2012-2016 than it was in 1987-1991. Both figures show a marked increase in the dispersion of industry profitability across workers.

One might think that part of the rise in inequality *within* labor as a group has been the result of a change in the distribution of workers across industries with high/low rents. There is suggestive evidence that workers with less education are more likely to work in firms with low rents now than in the past (because of the increased evidence of sorting between high fixed effect workers and high fixed effect firms from AKM models such as Song et al 2019). Does this also

[8] The pattern is very similar for the equal-weighted and value added-weighted Q across firms within each industry.

happen at the industry level? A preliminary analysis suggests it has not happened at the industry level. Figure C7 shows the share of college-educated or non-college educated workers employed in industries at each quartile of the distribution of median industry Q (as calculated from Compustat by Covarrubias et al 2019). Similarly, Figure C8 shows the share of college-educated or non-college educated workers employed in industries at each quartile of the distribution of profitability (gross operating surplus to fixed assets). By these metrics, it does not appear to be the case that there has been a sorting of lower education workers into lower-rent industries.

Figure C5: Allocation of employment by industry median Q, 1980-84 and 2013-17

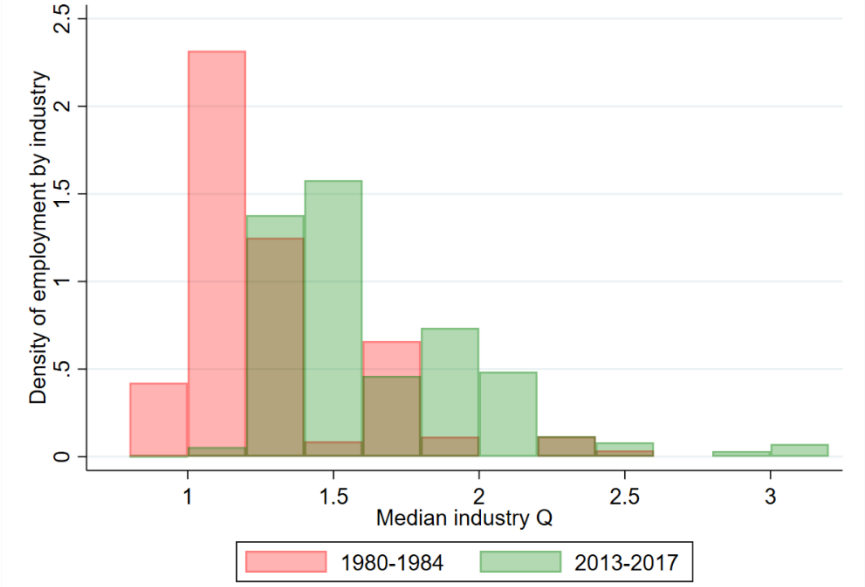


Figure C6: Allocation of employment by industry gross profit rate, 1980-84 and 2013-17

Figure C7: Employment of non-college and college educated workers, by industry median Q, 1980-84 and 2013-17

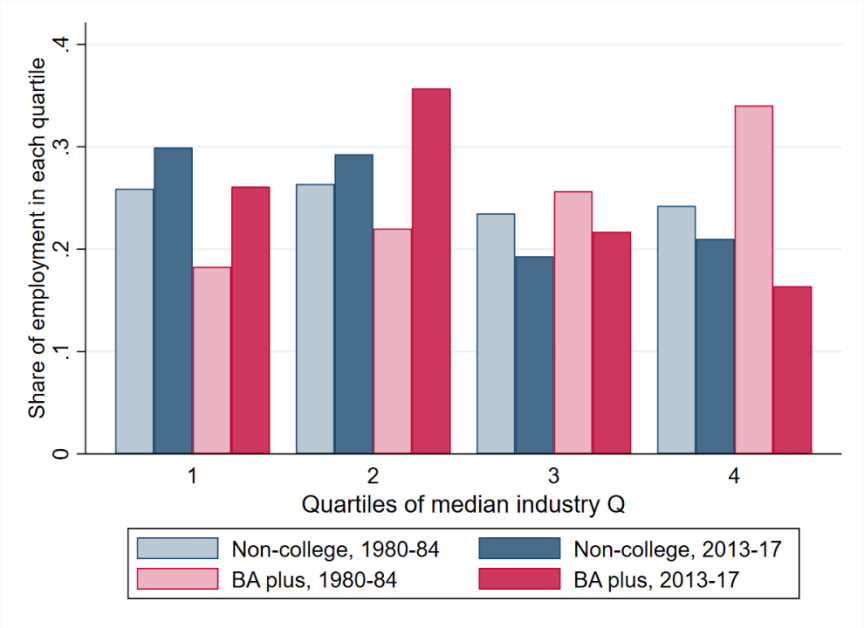
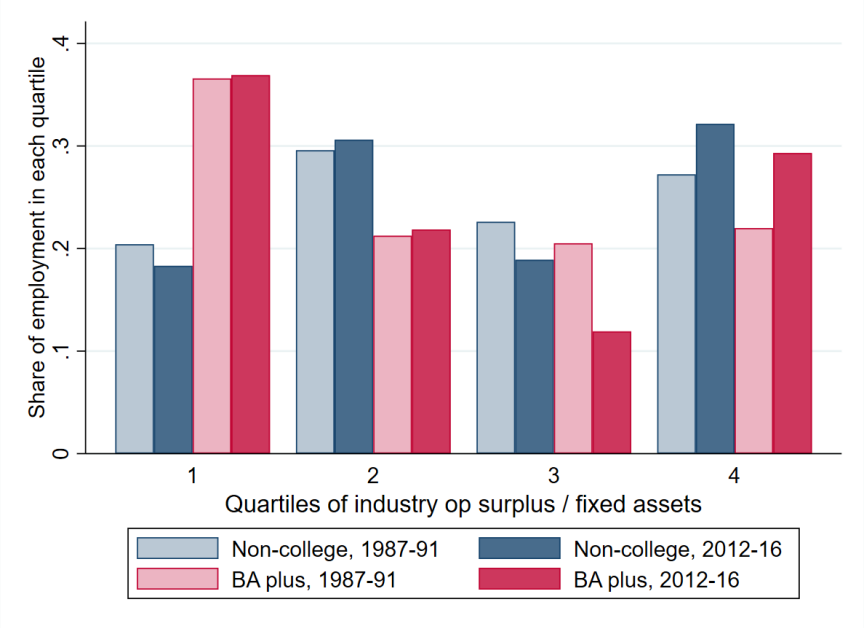


Figure C8: Employment of non-college and college educated workers, by industry gross profitability, 1987-91 and 2012-16



C.5. Labor rents by college/non-college

As we show in Section II.D., the decline in rent-sharing has affected non-college workers more than college workers. While industry rents declined in a relatively similar way for college and non-college workers, non-college workers were disproportionately affected by the fall in unionization and by the fall in large firm wage effects.

Figure C9 shows the private sector union coverage rate for workers with high school or with some college education, vs. workers with a four year college degree or postgraduate education. The decline has been much sharper for workers without college education. Figure C10 shows the estimated private sector union log wage premium for workers with no college vs. four-year college education (estimated from the CPS-ORG using the methodology described in Appendix section A1). Non-college workers have substantially higher union wage premia than college-educated workers, which makes the decline in unionization more costly for them.

Figure C11 shows the private sector firm wage effect, split by college and non-college workers. While the wage effect from medium sized firms (100-499 workers) stayed roughly constant for both groups over the period, the entire fall in the large firm wage premium (500+ workers) was concentrated on non-college workers.

Figure C12 shows that industry wage premia mostly moved in tandem for workers with and without college educations.

Figure C9: Private sector union coverage rates, by education group

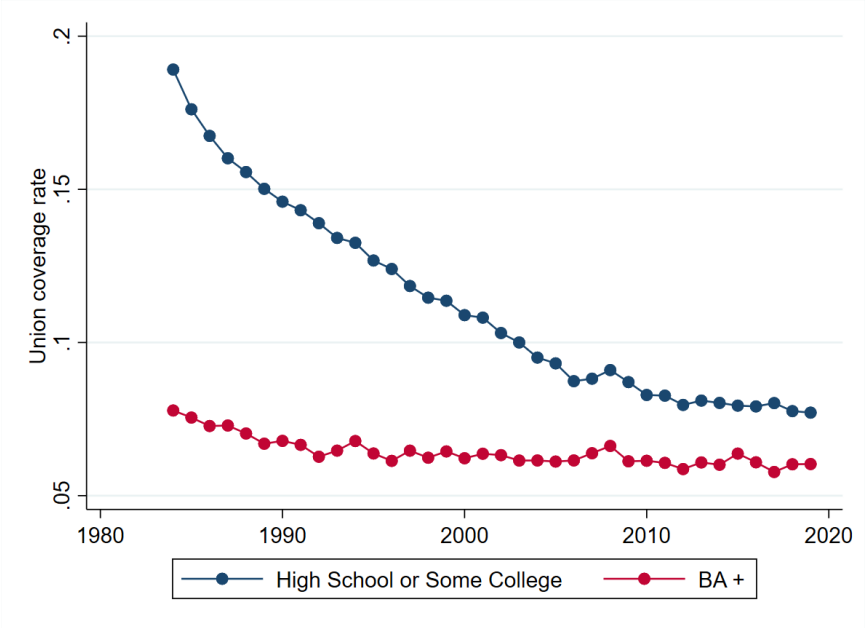


Figure C10: Private sector union log wage premium, by education group

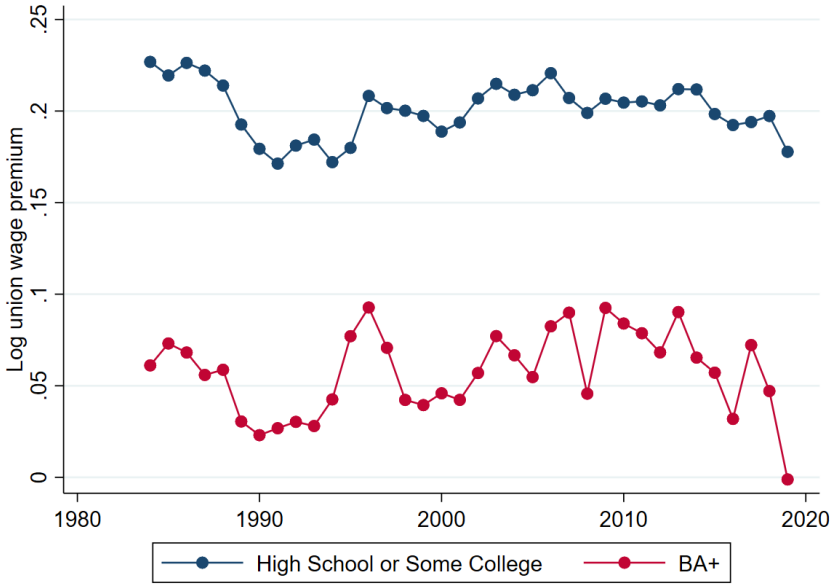


Figure C11: Private sector large firm wage effects, by education group

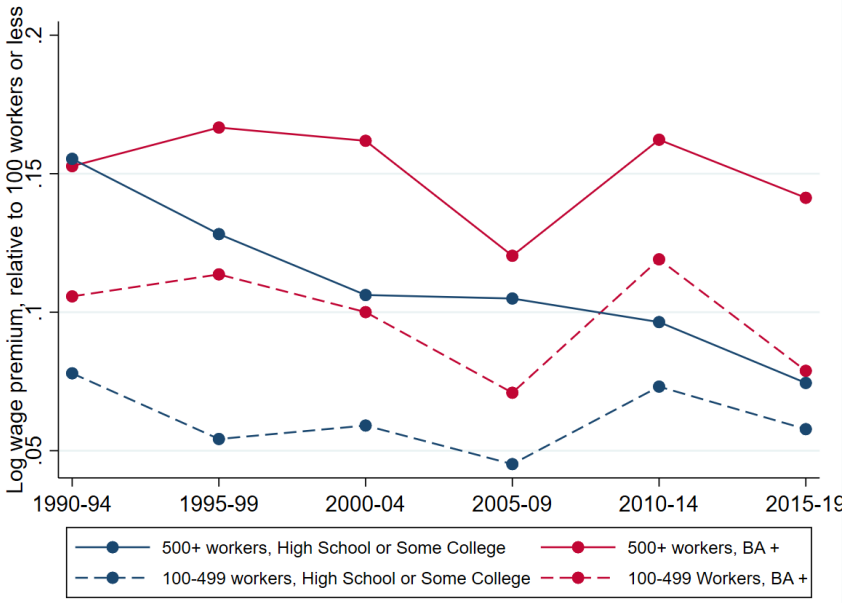
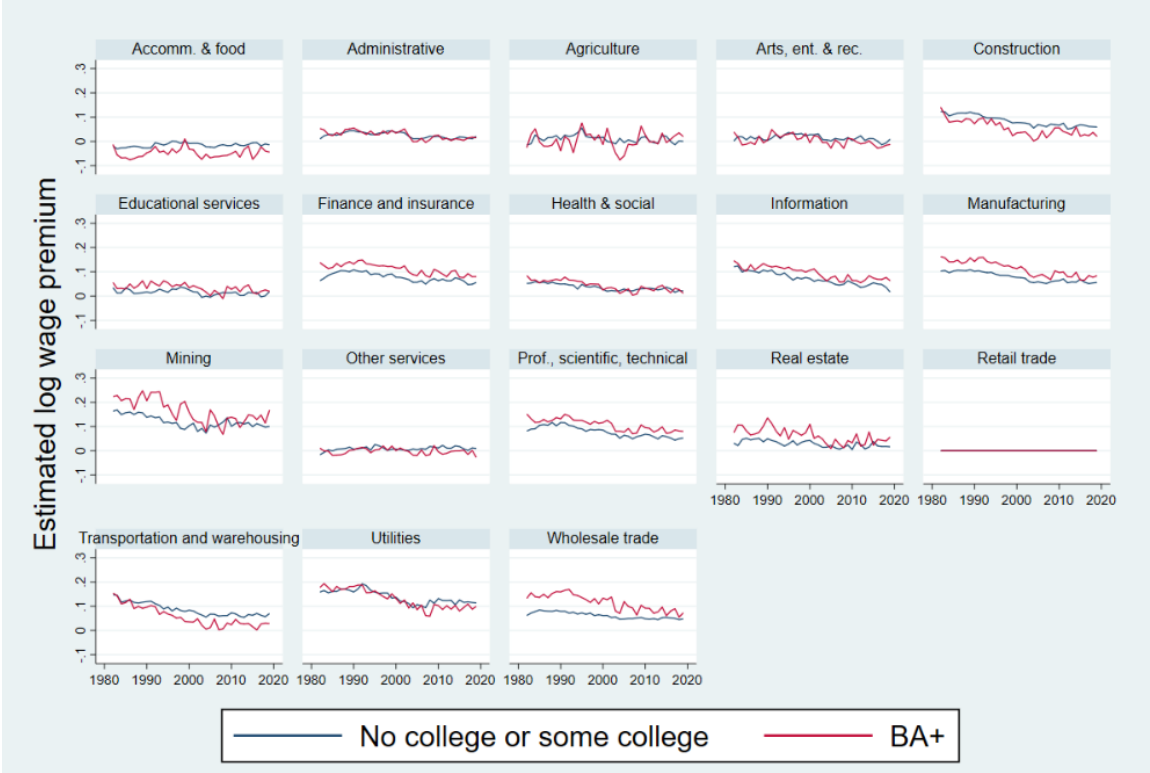


Figure C12: Industry wage premia, by education group



C.6. Decline in labor share, rise in capital share, and decline in investment-profits: gross measures

In the paper, we focus on measures of the labor share, capital share, and investment-profit ratio *net* of depreciation, for the nonfinancial corporate sector. Figures C13, C14, and C15 below replicate Figures 7, 8, and 18 in the paper, but for gross measures (without incorporating the effects of depreciation).

Figure C13: Labor rent share and compensation share of gross value added, nonfinancial corporate

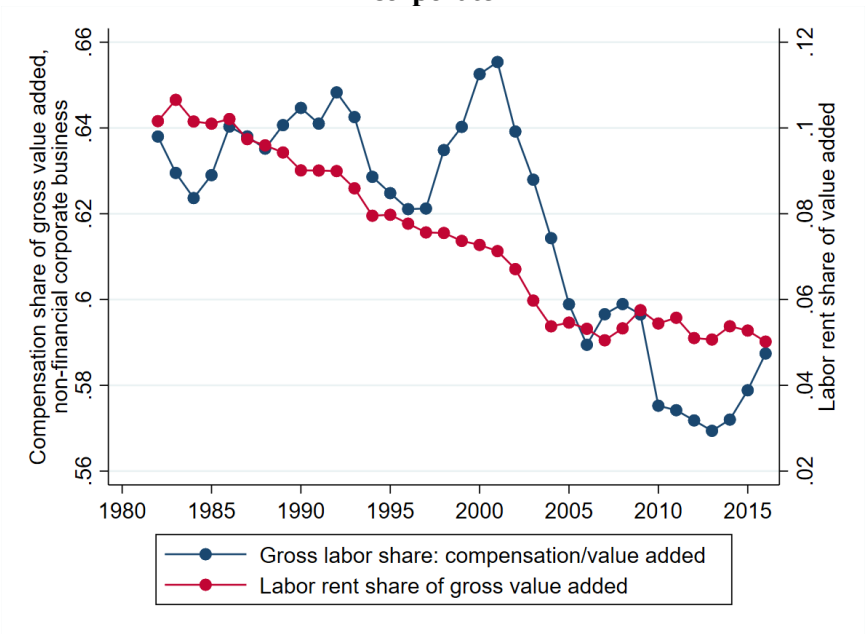


Figure C14: Capital share and "total profit" share of gross VA, nonfinancial corporate

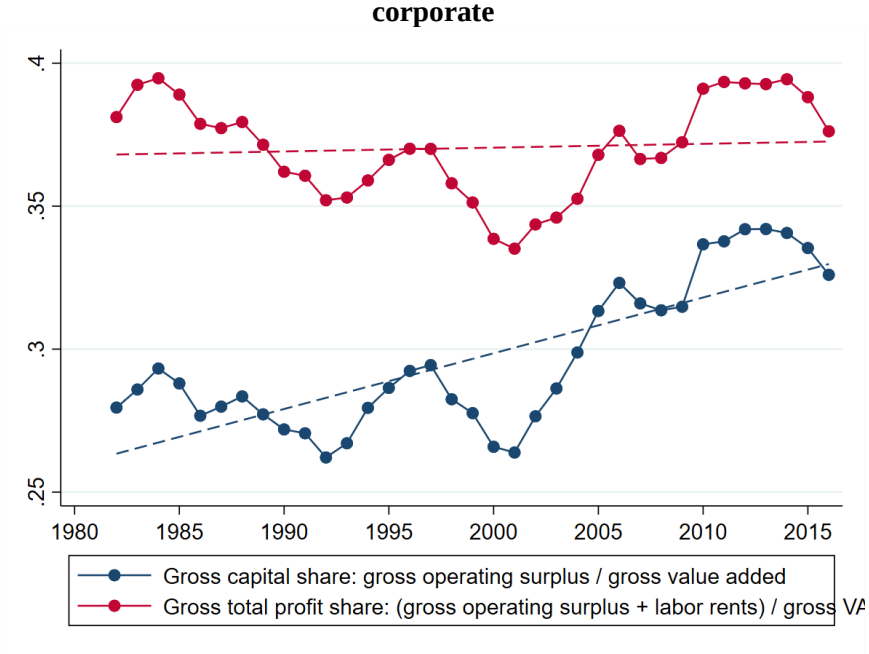
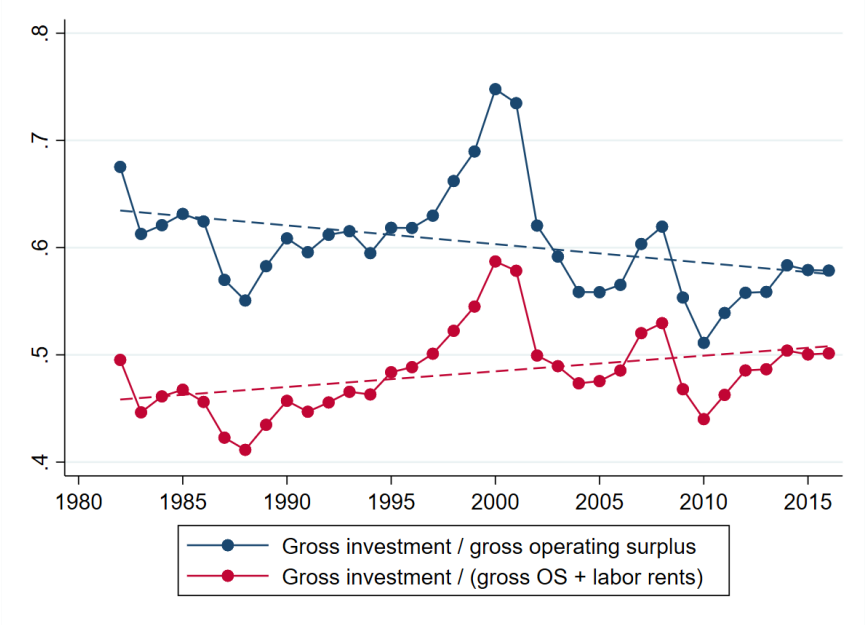


Figure C15: Gross investment to operating surplus, nonfinancial corporate



C.7. Industry-level analysis: unionization

In Table C1, we replicate Table 4 in the main paper, but using as our measure of worker power the industry unionization rate instead of our measure of imputed labor rents. The general pattern of results is similar to that in the main paper using labor rents.

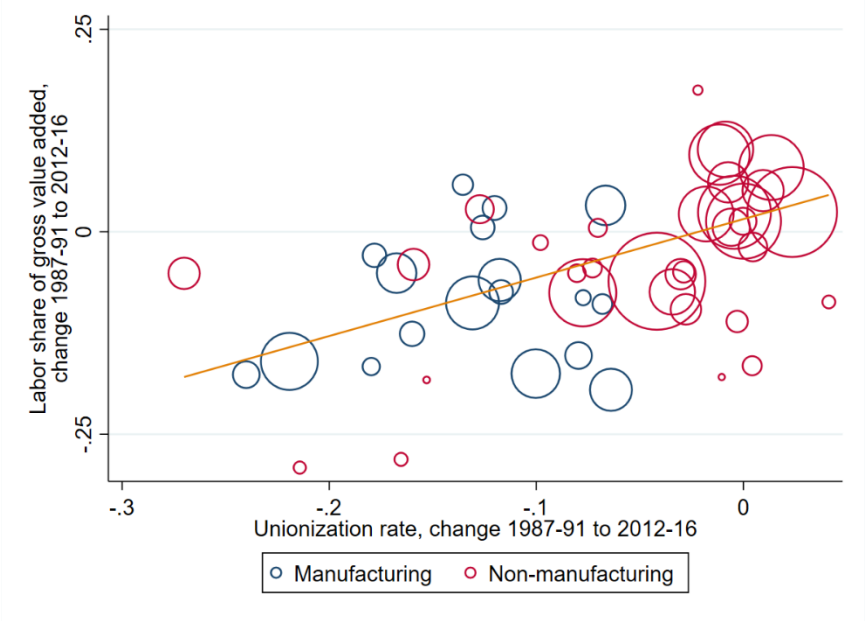
We note in particular that our regressions in Table C1 show a positive, relatively large, and statistically significant relationship between the industry unionization rate and labor share over 1987-2016. This is similar to the findings in Young and Zuleta (2017), albeit with a slightly different industry definition, timeframe, and regression specification.

Elsby, Hobijn, and Sahin (2013) find a positive correlation between the change in the union coverage rate and the change in the payroll share of value added over 1987-2011 across industries. They find that a 1 percentage point decline in the union coverage rate over the period was non-significantly associated with a 0.2 percentage point decline in the labor share, and argue that the point estimate suggests that the decline in unionization can only explain a small amount of the variation in the decline in the labor share. Since they do not emphasize the role of unions, based on their findings, it is worth comparing our results with theirs.

Therefore, we also carry out a very similar regression to Elsby et al (2013), over our slightly longer sample period – regressing the percentage point change in the compensation share

of gross and net value added from 1987-91 to 2012-16 on the percentage point change in the union coverage rate from 1987-91 to 2012-16 at the our BEA industry code level, weighting each observation by the industry's average share of value added over 1987-2016. The point estimates are 0.54 for the gross labor share, and 0.66 for the net labor share, both regressions with a p-value of 0.001 and R-squared of 0.19 – suggesting that nearly 20% of the variation in the industry-level labor share over the period can be explained by changes in unionization alone. This is visualized in Figure C16.

Figure C16: Change in unionization rate and change in labor share, by industry, 1987-2016



Bubble size represents industry share of value added, average over 1987-2016.

Table C1 Industry-level regressions, using unionization instead of imputed labor rents

This table is a replica of Table 4 in the main paper, but using the industry unionization rate instead of imputed labor rents as the measure of worker power at the industry level

Panel A: Regressions of labor shares and investment-profit on unionization and Compustat concentration. N = 1,189 (41 industries, 1987-2016)												
Dependent variable:	**Labor share of gross value added**				**Labor share of net value added**				**Investment to profit ratio**			
Industry unionization rate	0.09	0.03	0.43**	0.05	0.24	0.19	0.58**	0.27	0.15	0.14	0.31	0.34
	(0.22)	(0.24)	(0.10)	(0.13)	(0.27)	(0.29)	(0.19)	(0.18)	(0.31)	(0.33)	(0.26)	(0.61)
Avg top 20 sales concentration, imp-adj (Compustat)	-0.20*	-0.19*	-0.05	-0.04	-0.13	-0.12	-0.11	-0.09	0.28	0.29	-0.17	-0.16
	(0.08)	(0.08)	(0.07)	(0.07)	(0.10)	(0.10)	(0.12)	(0.13)	(0.21)	(0.22)	(0.22)	(0.23)
Fixed effects	*None*	*Year*	*Ind*	*Yr, Ind*	*None*	*Year*	*Ind*	*Yr, Ind*	*None*	*Year*	*Ind*	*Yr, Ind*
Panel B: Regressions of profitability measures on unionization and Compustat concentration. N=1,189 (41 industries, 1987-2016)												
Dependent variable:	**Gross profit rate**				**Aggregate Q**				**Median Q**			
Industry unionization rate	-0.30^{+}	-0.33^{+}	-0.02	-0.12	-1.45**	-1.37**	-0.93*	0.55	-1.14**	-1.01**	-1.39**	-0.02
	(0.15)	(0.17)	(0.14)	(0.16)	(0.39)	(0.41)	(0.43)	(0.65)	(0.31)	(0.32)	(0.42)	(0.50)
Avg top 20 sales concentration, imp-adj (Compustat)	-0.07	-0.07	0.03	0.03	0.19	0.17	-0.31	-0.30	0.32*	0.30^{+}	0.15	0.16
	(0.11)	(0.11)	(0.13)	(0.13)	(0.15)	(0.15)	(0.31)	(0.31)	(0.15)	(0.15)	(0.21)	(0.20)
Fixed effects	*None*	*Year*	*Ind*	*Yr, Ind*	*None*	*Year*	*Ind*	*Yr, Ind*	*None*	*Year*	*Ind*	*Yr, Ind*
Panel C: Regressions of labor shares and investment-profit on unionization and Census concentration. N = 174 (45 ind. for 1997, 2002, '07, '12)												
Dependent variable:	**Labor share of gross value added**				**Labor share of net value added**				**Investment to profit ratio**			
Industry unionization rate	-0.06	-0.10	0.43**	0.43**	0.05	0.01	0.76**	0.90**	-0.14	-0.25	1.36	1.58
	(0.25)	(0.27)	(0.13)	(0.14)	(0.30)	(0.32)	(0.26)	(0.28)	(0.89)	(0.98)	(0.86)	(1.12)
Avg top 20 sales concentration, imp-adj (Compustat)	-0.46**	-0.45**	-0.34**	-0.37**	-0.33*	-0.32^{+}	-0.72**	-0.80**	0.61	0.65	-1.09	-1.16
	(0.12)	(0.13)	(0.11)	(0.11)	(0.16)	(0.16)	(0.16)	(0.15)	(0.62)	(0.65)	(0.68)	(0.74)
Fixed effects	*None*	*Year*	*Ind*	*Yr, Ind*	*None*	*Year*	*Ind*	*Yr, Ind*	*None*	*Year*	*Ind*	*Yr, Ind*
Panel D: Regressions of profitability measures on unionization and Census concentration. N = 174 (45 ind. for 1997, 2002, '07, '12)												
Dependent variable:	**Gross profit rate**				**Aggregate Q**				**Median Q**			
Industry unionization rate	-0.70*	-0.77*	-0.08	-0.45*	-0.96^{+}	-1.22*	1.08	-0.15	-0.96*	-0.93*	-0.64^{+}	-0.67
	(0.34)	(0.38)	(0.21)	(0.20)	(0.53)	(0.55)	(0.80)	(1.00)	(0.38)	(0.40)	(0.36)	(0.51)
Avg top 20 sales concentration, imp-adj (Compustat)	-0.29	-0.27	0.41	0.55^{+}	-0.27	-0.16	-1.51^{+}	-0.83	0.13	0.14	-0.76	-0.30
	(0.27)	(0.27)	(0.28)	(0.28)	(0.28)	(0.29)	(0.83)	(0.72)	(0.21)	(0.22)	(0.45)	(0.40)
Fixed effects	*None*	*Year*	*Ind*	*Yr, Ind*	*None*	*Year*	*Ind*	*Yr, Ind*	*None*	*Year*	*Ind*	*Yr, Ind*

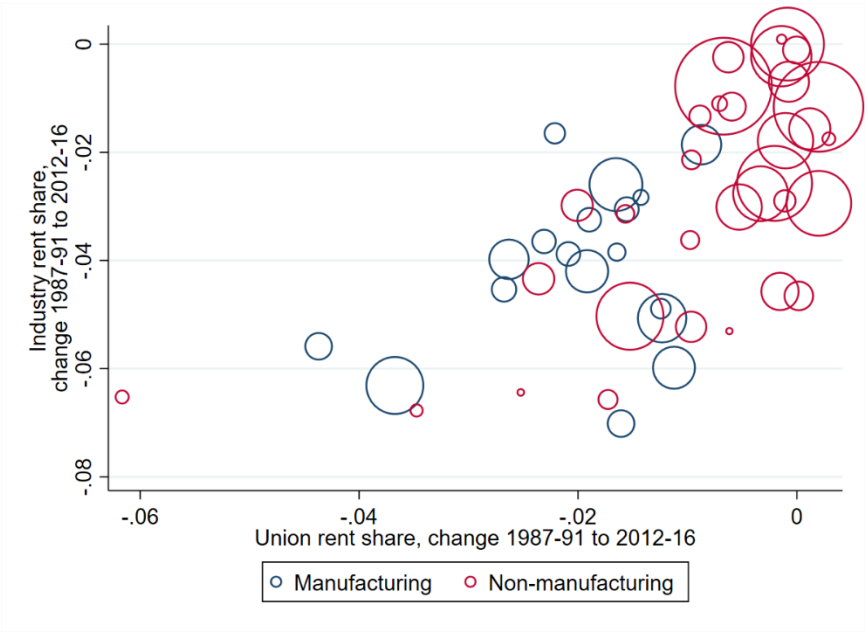
Robust standard errors, clustered at industry level, in parentheses. $^{+}$ *p<0.10, * p<0.05, ** p<0.01. Investment-profits are 98% winsorized.*

C.8. Relationship between industry, union, and firm size rents

We note in Section II that our measure of the union rent share only captures the direct effect of unions on unionized workers' wages, relative to non-unionized workers' wages. It is possible that our estimates of the industry and firm size rent shares pick up the "union threat effect", by which the possibility of unionization, or norms set by unions, raise wages even at non-unionized firms.

Industry- and firm-level trends in industry, union, and firm size rent shares are consistent with this. Industries which saw bigger declines in their union rent share also saw bigger declines in their industry rent share (Figure C17). At the level of 52 BEA industries, regressing the change in the imputed industry rent share over 1987-91 to 2012-16 on the change in the imputed union rent share over the same period gives a coefficient of 1.01, with a standard error of 0.16 and an R-squared of 43%. This also holds when regressing the industry rent share on the union rent share at an annual frequency, controlling for industry and year fixed effects and with standard errors clustered at the industry level: the coefficient estimate is 0.84, with a standard error of 0.11.

Figure C17: Change in industry rent share and union rent share, by industry, 1987-2016



Bubble size represents industry share of employment, 2012-2016 average. Graph shows 52 industries at the BEA industry code level.

At the state level, we can perform similar analyses. Regressing the change in the imputed industry rent share over 1984-88 to 2012-16 on the change in the imputed union rent share over the same period gives a coefficient of 0.70, with a standard error of 0.23 and an R-squared of 16%. Regressing the change in the imputed firm size rent share over 1984-88 to 2012-16 on the change in the imputed union rent share over the same period gives a coefficient of 0.49, with a standard error of 0.12 and an R-squared of 25%. These results are visualized in Figures C18 and C19. Regressions of the industry and firm size rent share on the union rent share at an annual frequency, controlling for state and year fixed effects and with standard errors clustered at the state level, gives coefficients (standard errors) of 0.37 (0.15) and 0.28 (0.09) respectively.

Figure C18: Change in industry rent share and union rent share, by state, 1987-2016

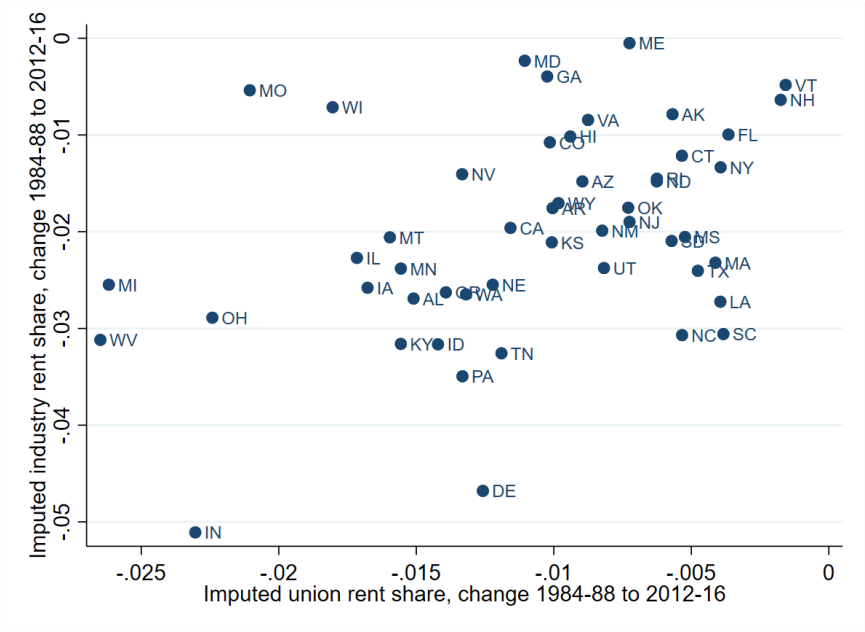
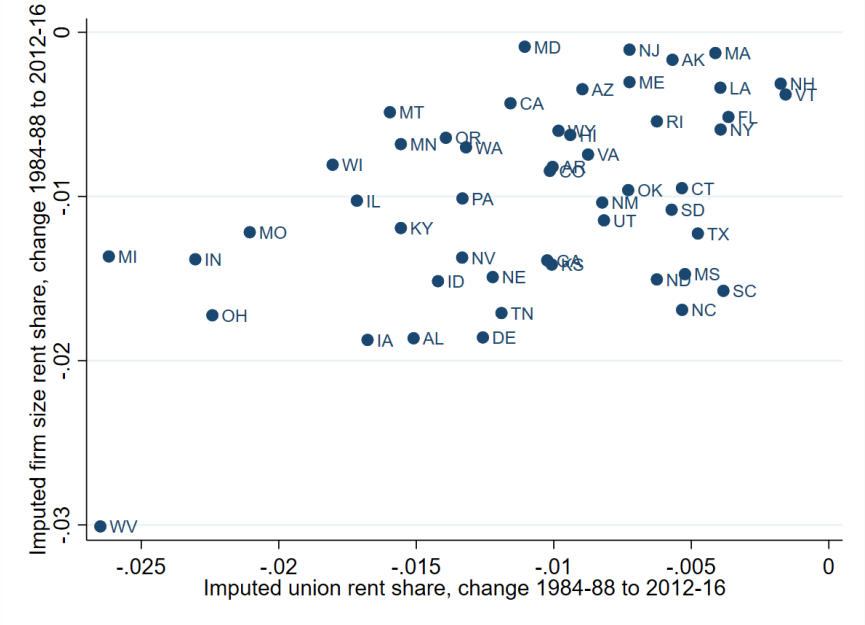


Figure C19: Change in firm size rent share and union rent share, by state, 1987-2016



C.9. Labor rents, unemployment, and labor market tightness

In Section IV we present evidence of a significant negative relationship between labor rents and unemployment at the state and industry level. Following Figura and Ratner (2015), we can also use JOLTS data on vacancy rates over 2000-2019 to test whether industries with bigger falls in our measures of labor power saw bigger increases in labor market tightness (vacancies/unemployment). The JOLTS database only reports data on relatively aggregated industries – 15 in total. As shown in Figures C20 and C21, the industries with the biggest falls in unionization rates over 2000/01-2018/19, or biggest falls in labor rent shares over 2000/01-2015/16, also saw the biggest increases in labor market tightness. (Note that 2000/01 and 2018/19 are particularly appropriate years to compare because aggregate V/U and unemployment was very similar in the two periods). In annual regressions of labor market tightness on measures of worker power over 2000-2016, with industry fixed effects, we similarly find that lower unionization rates or labor rent shares are significantly associated with higher vacancy-unemployment ratios. The coefficients suggest that the average fall in unionization was associated with a 10pp higher VU ratio, and the average fall in imputed labor rent share was associated with a 15.7pp higher VU ratio.

We also show in Figure C22 that industries with bigger falls in their unionization rate tended to see bigger falls in their unemployment rate over 1984-2019. (Analogous to Figure 15

in the main paper, which shows that industries with bigger falls in their imputed labor rent share tended to see bigger falls in their unemployment rate over 1988-2016).

Figure C20: Change in labor market tightness and the unionization rate, 2000-2019, by industry

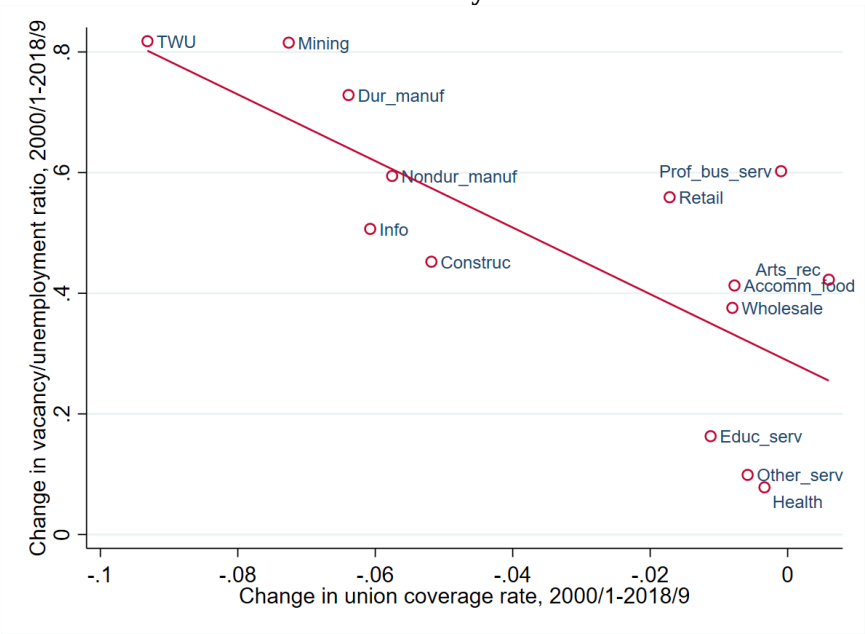
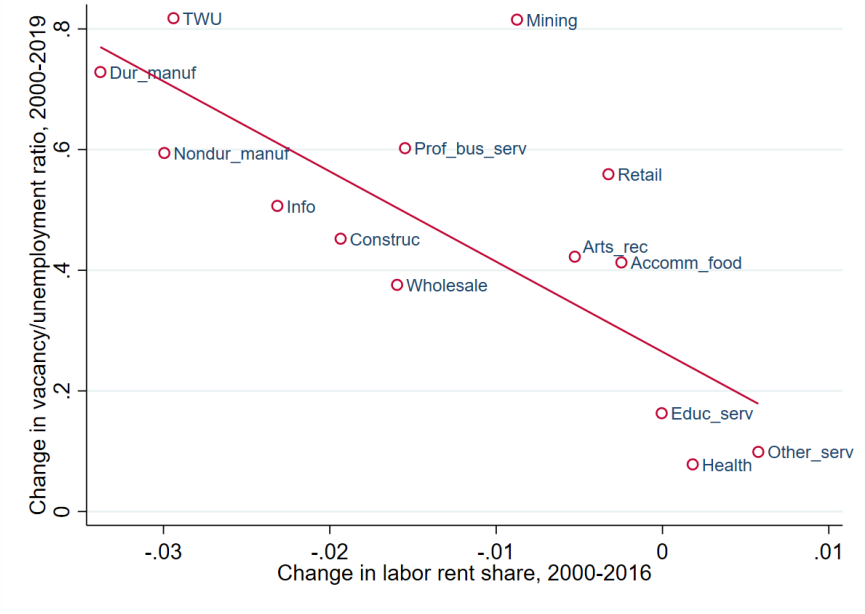


Figure C21: Change in labor market tightness and imputed labor rent share, by industry



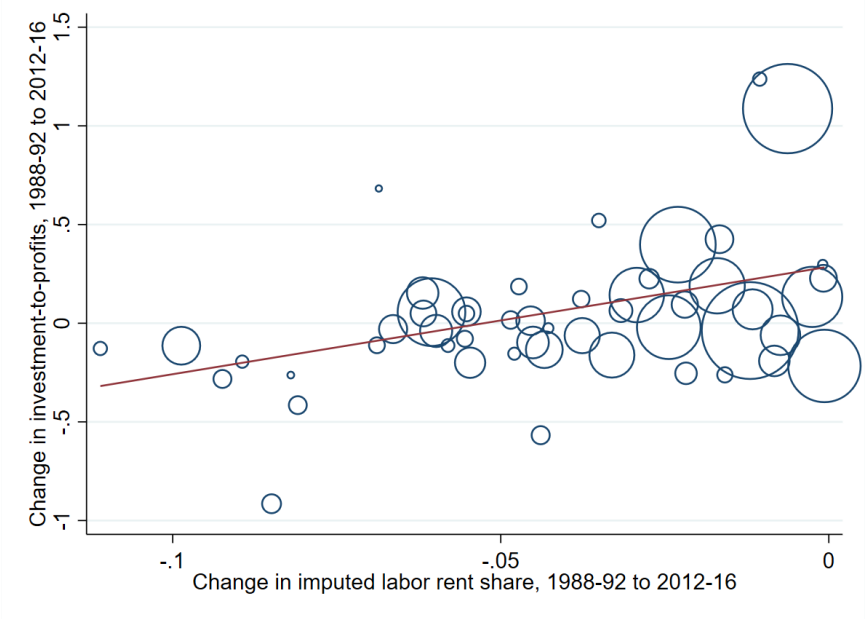
Notes to Figs C20-C21: Each dot is an industry (at the level of 15 JOLTS industry categories). Note that the observations for 2000-2001 are averages of monthly data from December 2000-December 2001 inclusive, as the JOLTS data only starts in December 2000. The observations for 2018-2019 are averages of monthly data from January 2018 to October 2019 inclusive. Red line is an employment-weighted line of best fit.

Figure C22: Change in unemployment and the unionization rate, by industry

C.10. Investment to profits and labor rents

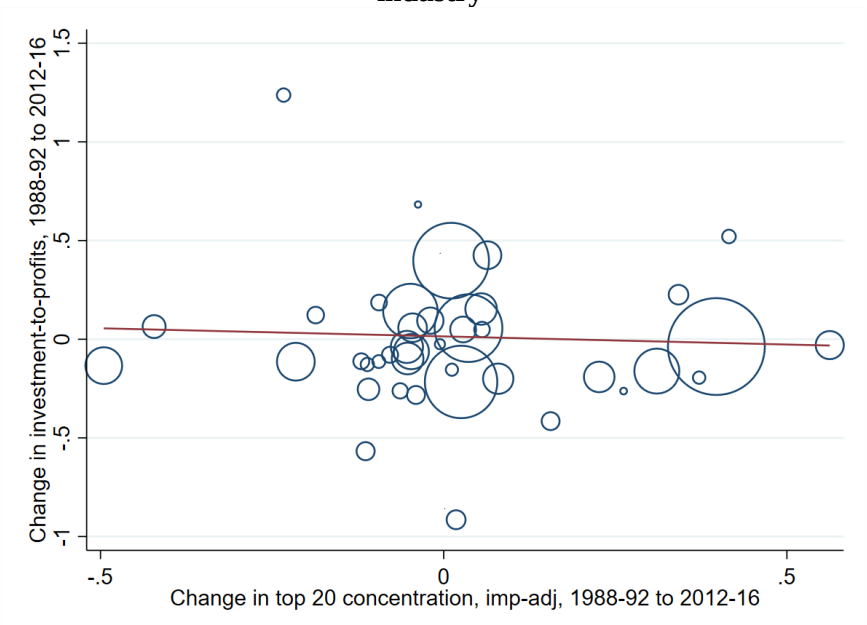
In section V we show that at the aggregate level, the decline in labor rents can explain the apparent decline in the ratio of investment to operating surplus in the nonfinancial corporate sector, and show that the ratio of investment to *total profits* – operating surplus, plus labor rents – has hardly declined at all. In Figure C23, we show that at the industry level, industries with larger declines in their labor rent share also saw larger relative falls in their investment-to-operating surplus ratio over 1988-2016. On the other hand, there is no relationship between top 20 import-adjusted sales concentration and the investment-to-profit ratio (Figure C24).

Figure C23: Change in investment-profits and imputed labor rent share, by industry



Notes: Each bubble is an industry (at the BEA industry code level), where the size of the bubble represents industry average employment over 2012-2016. The red line is an employment-weighted line of best fit.

Figure C24: Change in investment-profits and top 20 sales concentration (imp-adj), by industry



Notes: Each bubble is an industry (at the BEA industry code level), where the size of the bubble represents industry average employment over 2012-2016. The red line is an employment-weighted line of best fit.

C.11. Can the decline of labor rents account for the rise in the income share of the top 1%?

We calculate that labor rents as a % of gross value added in the nonfinancial corporate sector were 10.1% in 1982 and 5.0% in 2016. Nonfinancial corporate sector gross value added was a little less than 2/3 of national income over this period (65% in 1982, 58% in 2016, according to the BEA NIPA), which implies that labor rents declined by 3.7% of national income over 1982 to 2016.

Different authors come to quite different estimates for the magnitude of the increase in the income share of the top 1% over the last forty years, and the estimates are quite dependent on a number of methodological choices. Rather than take a stance on these choices, we use two of the most prominent recent estimates: Auten and Splinter (2019) estimate that the top 1% pre-tax income share rose by 4.9 percentage points over 1979 to 2014, while Piketty, Saez, and Zucman (2018) estimate that it rose by 9 percentage points.[9]

We perform two exercises with these data.

1. We assume that all labor rents that we measure accrued to the bottom 99% in the past, and were redistributed to the top 1% (whether as capital or labor income). In this case, our measure of the decline in labor rents could account for 3.7 of the 4.9 to 9 percentage points increase in the income share of the top 1%, so from 41% to 76% of the increase.

2. We assume that labor rents were redistributed as capital income across the entire income distribution (rather than just to the top 1%), in proportion to the distribution of capital income arising from firm ownership in 2016 (as estimated by Piketty, Saez, and Zucman 2018). Since the top 1% received 59% of total capital income in 2016, this would imply an increase in labor rents to the top 1% of income earners of 3.7*0.59 = 2.2% of national income, accounting for 24%-45% of the increase in the income share of the top 1% over recent decades.

Note that we are inclined to think our measure of the decline of labor rents in the nonfinancial corporate sector may be an *underestimate* of the decline of labor rents as a share of national income, since (a) labor rents may also have fallen in finance and in the non-corporate business sector, (b) union premia for non-wage compensation are greater than that for wages, but

[9] Auten and Splinter (2019) note that, since top income shares are very cyclical, one should compare similar points in the business cycle when looking at long changes in top income shares. They therefore suggest comparing 1979 and 2014.

we applied the union wage premium to non-wage compensation, and (c) the evidence appears to suggest that the union threat effect has positive spillover effects on other non-union wages, and our estimates may not capture all of this. This would suggest that our calculations above may be underestimates of the degree to which the decline in labor rents could account for the rise in the top 1% income share.

Appendix D: Further details on modified Farhi/Gourio accounting decomposition

D.1. Detailed writeup of modified Farhi/Gourio accounting decomposition

This section contains a more detailed writeup of our modified accounting decomposition based on Farhi and Gourio (2018). We are grateful that Farhi and Gourio provided their replication data and code online, such that it was easy to carry out our modified version of their decomposition.

Farhi and Gourio (2018) document six stylized macro-finance facts over recent decades:

1. Falling real risk-free interest rates
2. Rising profitability of private capital
3. Increasing valuation ratios
4. Slight fall in investment/output and investment/capital ratios
5. Slowing TFP and investment-specific productivity growth, and falling employment-population ratio
6. Falling labor share

They then decompose the degree to which these can be explained by five different factors: rising market power, rising unmeasured intangibles, rising risk premia, increased savings supply, and a slowdown of technological progress. Their model is an otherwise standard neoclassical growth model which incorporates macroeconomic risk, monopolistic competition, and the potential for mismeasurement of intangible capital. Their framework, however, does not take into account the possibility that workers may share in some of the rents generated by product market power, and that the degree of rent-sharing may have changed over time.

We incorporate a simple version of rent-sharing into the baseline Farhi/Gourio accounting framework (which does not include intangible capital). Farhi and Gourio find that rising market power plays a role in explaining the macro-finance facts of recent decades, but they

implicitly hold the degree of worker rent-sharing constant in their analysis (at zero). We do the opposite: we hold the degree of firm output market power constant in our analysis (setting the average markup at 1.15, the level that Farhi/Gourio estimate for the 2001-2016 period), and allow the degree of worker rent-sharing to vary.

We incorporate rent-sharing between labor and capital in the simplest way possible: the monopolistic firm still maximizes profits as before, hiring labor and capital in a competitive market. It then shares the rents or 'pure profits' between capital and labor, with share π_L going to labor. A decline in rent-sharing is modeled by a decline in π_L. This reduced-form approach can be micro-founded with an efficient bargain type model (Solow and MacDonald 1981) where workers, seeking to maximize total pay to labor, and shareholders, seeking to maximize their profits, jointly bargain over the firm's production decisions. Alternatively, the firm could be considered to be jointly managed in the (weighted average) interests of workers and shareholders.

Firm production decisions are the same in our framework as they would be in the Farhi/Gourio model without rent-sharing. This means that only a few equations change relative to the Farhi/Gourio model. We show these below:

Equation (20), the labor share:

$$s_L = \frac{w_t N_t}{Y_t} + \frac{\pi_L(Y_t - w_t N_t - R_t K_t)}{Y_t} = \frac{1 - \alpha + \pi_L(\mu - 1)}{\mu}$$

Equation (21), the measured capital share:

$$s_K = 1 - s_L = \frac{\alpha + (1 - \pi_L)(\mu - 1)}{\mu}$$

The measured capital share can be decomposed into the share representing monopoly rents, s_Π, and the 'true' capital share corresponding to remuneration for capital ownership, s_C:

$$s_\Pi = \frac{(1 - \pi L)(\mu - 1)}{\mu}$$

$$s_C = \frac{\alpha}{\mu}$$

Equation (24), Tobin's Q:

$$Tobin'sQ = \frac{P_t}{K_t/Q_t} = (1 + g_T)\left(1 + (1 - \pi_L)\frac{\mu - 1}{\alpha}\frac{r^* + \delta + g_Q}{r^* - g_T}\right)$$

Equation (26), the marginal product of capital:

$$MPK_t = \frac{\Pi_t}{K_t/Q_t} = \left(\frac{(1 - \pi_L)(\mu - 1) + \alpha}{\alpha}\right)(r^* + \delta + g_Q)$$

Equation (27), the spread between the marginal product of capital and the risk-free rate:

$$MPK - r_f = \delta + g_Q + \frac{(1 - \pi_L)(\mu - 1)}{\alpha}(r^* + \delta + g_Q) + r^* - r_f$$

The implications of our modifications for the comparative statics are shown in Table D1. As can be seen, there are only two differences in *sign* for key measurable moments of the data: lower-rent sharing is not predicted to affect the investment-output or capital-output ratios, whereas higher markups cause them to fall. In the US data, the investment-output ratio has fallen only very slightly and the share of non-residential investment in GDP has not fallen at all over 1984 to 2016. Meanwhile, the capital-output ratio has risen slightly (see Farhi and Gourio Table 1).

Table D1: Different predictions of FG vs. SS

	Higher Markups μ	Lower rent-sharing π_L
Labor share	↓	↓
'True' capital share	↓	no change
Pure profit share	↑	↑
Investment-output ratio	↓	no change
Capital-output ratio	↓	no change
Spread between ret. on K and RF rate	↑	↑
Tobin's Q	↑	↑

Farhi and Gourio estimate nine key parameters in their model, targeting nine key moments, for the periods 1984-2000 and 2001-2016. We denote their baseline accounting decomposition "FG".

The parameters they estimate are:

1. β, the discount factor
2. p, the probability of an economic crisis or "disaster"
3. δ, the depreciation rate of capital
4. α, the Cobb-Douglas parameter

5. g_P, the growth rate of the population
6. g_Z, the growth rate of TFP
7. g_Q, the growth rate of investment-specific productivity
8. $\bar{N}$, the labor supply parameter
9. μ, the markup

These parameters are estimated targeting nine moments:

1. Gross profitability $\frac{\Pi}{K}$
2. Gross share of income going to capital $\frac{\Pi}{Y}$
3. Investment-capital ratio $\frac{I}{K}$
4. Risk-free rate *RF*
5. Price dividend ratio *PD*
6. Growth rate of population
7. Growth rate of TFP
8. Growth rate of investment prices
9. Employment-population ratio

We replicate the baseline Farhi/Gourio ("FG") decomposition. We then modify the Farhi/Gourio approach to allow for changing rent-sharing between capital and labor, *instead* of changing total rents (monopoly power). To do this, we hold the markup constant at 1.15, which is the level of the markup that Farhi/Gourio estimate for the second period in their study (2001-2016). We instead allow the parameter governing rent-sharing with labor to change (π_L), and estimate this alongside the other 8 Farhi/Gourio parameters, targeting the same empirical moments. We denote this approach as "SS" going forward.

Identification in our modified accounting decomposition is nearly identical to that in Farhi/Gourio. As with theirs, the identification is nearly recursive. Some parameters are obtained directly, as their counterparts are assumed to be observed: population growth g_N, investment price growth (the inverse of g_Q), and the employment-population ratio $\bar{N}$. The growth rate g_Z is chosen to roughly match measured TFP (but also depends on α, the estimated Cobb-Douglas parameter). The depreciation rate δ is chosen to match $\frac{I}{K}$ using the balanced growth relation (eq. 18 in F/G), and the Gordon growth formula is used to infer the expected return on risky assets r^*.

Our approach differs from Farhi/Gourio *only* when we identify the parameters α and π_L, using our modified versions of equations (20) and (27) above. The labor share s_L and the marginal product of capital (approximated by average profitability of capital $\frac{\Pi}{K}$) are the observables, and we set the markup $\mu = 1.15$. Since we have estimates for r^*, δ, g_Q, we can identify α and π_L from this pair of equations.

Identification then continues as in Farhi/Gourio, using data on the risk-free rate to infer the equity premium, and separately inferring discount factor β, risk aversion θ, and quantity of risk ξ (making assumptions about these variables and the intertemporal elasticity of substitution exactly as in the paper). Note that these choices do not affect inferences about α or π_L.

Table D2 compares the parameter estimates in the Farhi/Gourio baseline model ("FG") compared to our model ("SS"). *(Table 2 in the main paper is a truncated version of this table. In Table 2, we only show the parameters which were estimated to have changed).* Note that the majority of estimated parameters are identical or very similar across the two specifications, reflecting the recursive identification procedure described above. The only differences are in the rent-sharing parameter and markup parameter (by construction), and in the Cobb-Douglas parameter α and TFP growth parameter g_Z.

In the Farhi/Gourio model, the markup is estimated to rise from 1.08 in the period 1984-2000 to 1.15 in the period 2001-2016 (implicitly holding rent-sharing constant at zero in both periods). In our model, holding the markup constant at 1.15 in both periods, rent-sharing with labor is estimated to fall from 0.44 in the period 1984-2000 to 0.02 in the period 2001-2016. In contrast to the Farhi/Gourio model, our model also features a small decline in the Cobb-Douglas parameter α, suggesting a small amount of labor-biased technical change (FG estimates no change in α). Our model estimates a smaller decline in the rate of TFP growth than the FG model. Common to both models are an increase in the discount factor, reflecting higher savings supply; an increase in macroeconomic risk (disaster probability); and an increase in the rate of depreciation. Note that these factors are identical in both exercises by construction of our modification exercise.

Table D2: Estimated parameters and changes between samples

Parameter	Symbol	Model	First Sample (1984-2000)	Second Sample (2001-2016)	Difference
Discount factor	β	FG	0.961	0.972	0.012
		SS	0.961	0.972	0.012
Disaster probability	p	FG	0.034	0.065	0.031
		SS	0.034	0.065	0.031
Depreciation	δ	FG	2.778	3.243	0.465
		SS	2.778	3.243	0.465
Cobb-Douglas	α	FG	0.244	0.243	-0.000
		SS	0.260	0.244	-0.016
Population growth	g_P	FG	1.171	1.101	-0.069
		SS	1.171	1.101	-0.069
TFP growth	g_Z	FG	1.298	1.012	-0.286
		SS	1.233	1.010	-0.223
Investment in technical growth	g_Q	FG	1.769	1.127	-0.643
		SS	1.769	1.127	-0.643
Labor supply	$\bar{N}$	FG	62.344	60.838	-1.507
		SS	62.344	60.838	-1.507
Rent-sharing with labor	π_L	FG	–	–	–
		SS	0.441	0.022	-0.419
Markup	μ	FG	1.079	1.146	0.067
		SS	–	–	–

In Table D3 we show the estimated contribution of each parameter to changes in the model-implied moments, replicating Table 4 of Farhi/Gourio. For these decompositions we use the method that Farhi and Gourio use to estimate the contributions of each parameter to each change in the key moments. As Farhi/Gourio note: "because our model is non-linear, this is not a completely straightforward task; in particular, when changing a parameter from a first subsample value to a second subsample value, the question is at which value to evaluate the other parameters (for example, the first or second subsample value). If the model were linear, or the changes in parameters were small, this would not matter; but such is not the case here, in particular for the price-dividend ratio". They therefore report the *average contribution* over all possible orders of changing parameters, as we move from the first to the second subsamples.

In both the "FG" and the "SS" case, the decline in the risk free rate is primarily explained by a rise in savings supply (decline in discount factor β) and an increase in disaster risk *p*. This increase in savings supply should, all else equal, decrease average profitability of capital $\frac{\Pi}{K}$ by 2

percentage points. In reality, the average profitability of capital has risen a little. The baseline Farhi/Gourio model reconciles the rise in savings supply and small rise in average profitability of capital with a combination of higher macroeconomic risk and higher markups. In the “SS” case, instead, the two are reconciled with higher macro risk and lower rent-sharing with labor.

In the “FG” case, the change in markups accounts for the bulk of the increase in price-earnings ratios and in Tobin's Q over the period. In the “SS” case, this is instead achieved by the fall in rent-sharing with labor. The “SS” model accounts for the rise in the Price-Dividend ratio slightly differently as compared to the “FG” model, with a slightly larger role for the decline in the Cobb-Douglas parameter α and a slightly smaller role for the decline in TFP growth g_Z.

The increase in the share of income going to capital (the “measured capital share”) and its counterpart, the decline in the labor share, is entirely explained by higher markups in the “FG” case: higher markups create a wedge between the marginal product and the return for both labor and capital, pushing down the labor share and “pure” capital share, but increasing the “pure” profit share. In the “SS” case, the increase in the measured capital share/decline in the labor share is primarily explained by lower rent-sharing with labor; at the same time, the decline in the Cobb-Douglas parameter α acts to increase the labor share and reduce the capital share, partly offsetting the decline in the labor share that would have occurred from the estimated decline in rent-sharing alone.

Finally, in the “FG” case the capital-output ratio, investment-output ratio, and growth rates of output and investment are lower than they otherwise would have been if markups had not risen. In contrast in the “SS” case, the degree of rent-sharing between capital and labor in our model does not affect firms' production or investment decisions.

D.2. Plausibility of estimated rent-sharing parameter in Farhi/Gourio accounting decomposition

Our estimation suggests that the rent-sharing parameter was 0.44 in the 1980s-1990s. How plausible is this? To compare this to estimates from the literature, we need to translate it into the rent-sharing elasticities estimated in the empirical literature.

Following Card et al (2018), note that under certain assumptions the elasticity of wages with respect to an increase in total rents (pure profits), ξ_R, is equivalent to the share of labor rents in wages. Then, the elasticity of wages with respect to *value added* is $\xi_{VA} = \xi_R \cdot \frac{VA}{Rents}$.

In our accounting decomposition, the equilibrium share of rents in wages in the first period (1984-2000) is 0.09, implying an elasticity of wages with respect to rents of $\xi_R = 0.09$ and an elasticity of wages with respect to value added of $\xi_{VA} = 0.44$. These estimates are not implausibly high compared to the (few) well-identified empirical estimates of rent-sharing elasticities in the US (many of which are summarized in Card et al (2018)).

Blanchflower, Oswald, and Sanfey (1996), for example, found an elasticity of 0.01-0.06 for the transmission of industry-level profits per worker into wages in U.S. manufacturing industries. Estevao and Tevlin (2003) also studied U.S. manufacturing industries, instrumenting for shocks to industry demand using increases in output of large downstream sectors: they found a rent-sharing elasticity of 0.29 for value added per worker and 0.14 for profits per worker (as reported in Card et al (2018)). Barth, Bryson, Davis, and Freeman (2016) use the Longitudinal Business Database, instrumenting for demand shocks using output of the same industry in other regions, and find an elasticity of wages with respect to sales per worker of 0.16. Kline, Petkova, Williams, and Zidar (2019) use the granting of patents to firms as an instrument for a profit/rent shock, and estimate an average rent-sharing parameter of 0.3. Lamadon, Mogstad, and Setzler (2019) find that a 10% increase in firm value added results in 1.4% higher wages.

Table D3: Contributions of estimated parameters to model moments

		Model-implied moments			Contributions of each parameter									
	Model	1984-2000	2001-2016	Difference	β	p	δ	α	g_P	g_Z	g_Q	$\bar{N}$	π_L	μ
MPK-RF spread	FG	11.22	15.24	4.02	-0.66	2.39	0.68	0.00	0.00	-0.10	-1.05	0.00		2.76
	SS	11.22	15.24	4.02	-0.66	2.39	0.68	0.26	-0.00	-0.08	-1.05	0.00	2.48	
...of which, depreciation	FG	4.55	4.37	-0.18	0.00	0.00	0.47	0.00	0.00	0.00	-0.64	0.00		0.00
	SS	4.55	4.37	-0.18	0.00	0.00	0.47	0.00	0.00	0.00	-0.64	0.00	0.00	
...of which, market power	FG	3.39	5.55	2.17	-0.59	0.24	0.21	0.00	-0.00	-0.09	-0.35	0.00		2.73
	SS	6.05	5.68	-0.37	-0.76	0.31	0.28	0.34	-0.00	-0.09	-0.45	0.00	0.00	
...of which, risk premium	FG	3.15	5.23	2.08	-0.05	2.14	0.00	-0.00	-0.00	-0.01	-0.00	0.00		0.00
	SS	3.15	5.23	2.08	-0.05	2.14	0.00	-0.00	-0.00	-0.01	-0.00	0.00	0.00	
Equity return	FG	5.85	4.90	-0.96	-1.22	0.56	0.00	-0.00	-0.00	-0.19	-0.10	0.00		0.00
	SS	5.85	4.90	-0.96	-1.22	0.56	0.00	-0.04	-0.00	-0.15	-0.11	0.00	0.00	
Equity premium	FG	3.07	5.25	2.18	0.00	2.18	0.00	0.00	0.00	0.00	0.00	0.00		0.00
	SS	3.07	5.25	2.18	0.00	2.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Risk-free rate	FG	2.79	-0.35	-3.14	-1.22	-1.62	0.00	-0.00	-0.00	-0.19	-0.10	0.00		0.00
	SS	2.79	-0.35	-3.14	-1.22	-1.62	0.00	-0.04	-0.00	-0.15	-0.11	0.00	0.00	
Price-dividend ratio	FG	42.34	50.11	7.78	30.67	-13.19	0.00	-0.02	-1.86	-5.07	-2.76	0.00		0.00
	SS	42.34	50.11	7.78	30.56	-13.13	0.00	-0.96	-1.85	-3.97	-2.87	0.00	0.00	
Price-earnings ratio	FG	17.85	25.79	7.94	10.16	-4.57	-0.35	0.00	-0.59	-1.47	-0.34	0.00		5.08
	SS	17.85	25.79	7.94	10.11	-4.54	-0.35	0.23	-0.58	-1.15	-0.37	0.00	4.58	
Tobin's Q	FG	2.50	3.84	1.34	1.05	-0.48	0.11	0.00	-0.08	-0.28	-0.31	0.00		1.34
	SS	2.50	3.84	1.34	1.03	-0.47	0.11	0.09	-0.08	-0.22	-0.32	0.00	1.20	
Labor share	FG	70.11	66.01	-4.10	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00		-4.13
	SS	70.11	66.01	-4.10	0.00	0.00	0.00	1.35	0.00	0.00	0.00	0.00	-5.46	
'Pure' capital share	FG	22.59	21.24	-1.35	0.00	0.00	0.00	-0.03	0.00	0.00	0.00	0.00		-1.33
	SS	22.59	21.24	-1.35	0.00	0.00	0.00	-1.35	0.00	0.00	0.00	0.00	0.00	
'Pure' profit share	FG	7.30	12.76	5.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		5.46
	SS	7.30	12.76	5.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.46	
K/Y	FG	2.13	2.28	0.15	0.29	-0.12	-0.11	-0.00	-0.00	0.04	0.18	-0.00		-0.13
	SS	2.13	2.28	0.15	0.29	-0.12	-0.11	-0.13	0.00	0.04	0.18	-0.00	0.00	
I/Y	FG	17.28	16.50	-0.78	2.20	-0.90	0.23	-0.02	-0.16	-0.52	-0.59	-0.00		-1.03
	SS	17.28	16.50	-0.78	2.20	-0.90	0.23	-1.15	-0.16	-0.41	-0.61	-0.00	0.00	
Detrended Y (% change)	FG	–	–	-0.30	4.18	-1.70	-1.52	-0.07	-0.00	0.65	2.56	-2.45		-1.95
	SS	–	–	-2.36	4.38	-1.78	-1.59	-4.16	0.00	0.54	2.69	-2.45	0.00	
Detrended I (% change)	FG	–	–	-4.95	17.18	-6.98	-0.12	-0.20	-0.94	-2.45	-0.96	-2.45		-8.02
	SS	–	–	-7.01	17.38	-7.05	-0.19	-10.93	-0.94	-1.91	-0.91	-2.45	0.00	

Appendix E: Quantitative implications of the decline in worker power for the NAIRU

In Section IV of the paper, we argue that the decline in worker power should have been expected to reduce the NAIRU. Here, we use a number of simple exercises to illustrate the possible magnitude of the decline in the NAIRU induced by the decline in worker power.

First, we use the model in Summers (1988) which argues that the equilibrium rate of unemployment is a function of the degree of worker rent-sharing power (indexed by the share of workers with power β and the wage premium they receive μ), the level of the value of unemployment relative to the value of work *b*, and the efficiency wage parameter α (the elasticity of worker productivity to the relative wage)**:**

$$u = \frac{\alpha + \mu\beta}{(1 - b)(1 + \mu\beta)}$$

Summers sets $\alpha = 0.06$ and *b*=0. Using these, and plugging in the changes in the unionization rate (for β) and union wage premium (for μ) over 1982 to 2019, would predict a 3.5 percentage point decline in the equilibrium unemployment rate. Using the larger changes in the degree of rent-sharing that we estimate in prior sections – rather than just the decline in unionization – or using larger values for *b*, the value of unemployment, or smaller values for α*,* the efficiency wage parameter, would predict even larger declines in equilibrium unemployment.

A second exercise uses the model in Johnson and Layard (1986). They lay out a model of wait unemployment, where the availability of high wage union jobs incentivizes workers to search for union jobs rather than accept a lower-paid job in the competitive sector. In their simple model, the NAIRU is determined as follows:

$$U = \frac{1}{\frac{\delta(1 - \rho)}{QmP} + 1}$$

where *P* is the unionization rate, *m* is the union wage premium (markup over the competitive wage), *Q* is the rate at which unionized workers leave their jobs, δ is the discount rate, and ρ is the replacement rate of unemployment benefits (the ratio of the value of being unemployed relative to the competitive wage). Plugging the decline in the unionization rate and union wage premium from 1982 to 2019 into this simple equation, alongside a replacement rate of benefits of

0.5, discount rates of between 3 and 8 percent, and a separation rate of unionized workers of between 2 and 4 percent, would yield a fall in the NAIRU of 0.9-2.2 percentage points. Once again, using the full estimated reduction in labor rents would increase this estimate, whereas a higher replacement rate of benefits would reduce the fall in the NAIRU.

Finally, Akerlof, Dickens, and Perry (1996) specify a Phillips curve equation where inflation π is a product of the expected inflation rate π^E, unemployment u, the worker rent-sharing parameter a (in a simple bargaining-over-surplus model), firms' product market markup $\frac{\beta-1}{\beta}$, and a function of the degree of downward nominal wage rigidity S:

$$\pi_t = \pi_t^E + c - au_t + \frac{\beta}{\beta - 1} S_t$$

In the absence of downward nominal wage rigidity, this suggests that the slope of the Phillips curve is equivalent to the degree of worker rent-sharing power. The decline in the slope of the Phillips curve estimated by Blanchard, Cerutti, and Summers (2015) was 0.23 from the 1960s until the 2010s. This would be consistent with the magnitude of the decline in worker rent-sharing that we have identified earlier in this paper. The decline in the worker rent-sharing parameter that was estimated to be consistent with changes in other macro variables like the labor share, in our accounting decomposition, was 0.42 over the 1980s to 2010s; and our estimated decline in imputed labor rents would have been consistent with a decline in the worker rent-sharing parameter of between 0.22 and 0.41 over the 1980s to 2010s (under the assumption of a constant aggregate markup of between 1.1 and 1.2 over the period).

What do these exercises suggest? While these models are by design not able to provide precise estimates, they suggest that in very loosely disciplined models with several free parameters it is very easy to obtain very large impacts of a decline in worker power – of the magnitude we have observed – on the NAIRU and the slope of the Phillips Curve.

Appendix F: Markup measurement and labor rents

Baqaee and Farhi (2020) outline three measures for firm-level markups in the U.S. data: (1) the accounting profits approach, (2) the user cost approach, (3) the production function estimation approach. All three of these methods for measuring markups include some measure of costs, *including labor costs*, in the denominator. This means that if rent-sharing with labor falls, measured labor costs will fall, leading to an increase in measured markups without any changes in the underlying product market power of a firm. This is illustrated in more detail below.

Accounting profits approach: This is the simplest approach to markup measurement. If one assumes that operating income is equal to profits, this implies that markups are equal to sales divided by costs. Baqaee and Farhi (2020) use the expression

$$operatingsurplus_{i,t} = \left(1 - \frac{1}{\mu_{i,t}}\right) sales_{i,t}$$

to back out firm-level markups μ, measuring operating surplus as *operating income minus depreciation* from Compustat data. Firm-level operating income is measured as revenue minus costs, where costs include labor costs. If rent-sharing with labor falls, payments made to workers for a given unit of work will fall, leading measured labor costs to fall. This leads mechanically to an increase in measured markups.

User cost approach: The user cost approach, used by Gutierrez and Philippon (2017) and Baqaee and Farhi (2020), is similar to the accounting profits approach – but, with a more sophisticated consideration of the cost of capital. In this approach markups are estimated as the ratio of sales to total average costs, which are calculated as operating expenses plus an imputed cost of capital. Markups can be estimated from the expression

$$operatingsurplus_{i,t} = r_{kt,t} K_{i,t} + \left(1 - \frac{1}{\mu_{i,t}}\right) sales_{i,t}$$

where $operatingsurplus_{i,t}$ is the operating income of the firm after depreciation and minus income taxes, $r_{kt,t}$ is the user-cost of capital and $K_{i,t}$ is the quantity of capital used by firm *i* in period *t*. Once again, since firm-level operating income is measured as revenue minus costs, where costs include labor costs, then if rent-sharing with labor falls, measured markups will mechanically increase.

Production function estimation approach : The production function estimation approach, used by De Loecker, Eeckhout, and Unger (2020) (and based on De Loecker and Warzynski (2012)), estimates firm-level markup as a function of the estimated elasticity of output with respect to variable inputs, θ_{it}^{v}, and the ratio of sales to variable costs, $\frac{P_{it}Q_{it}}{P_{it}^{V}V_{it}}$:

$$\mu_{it} = \theta_{it}^{v} \frac{P_{it}Q_{it}}{P_{it}^{V}V_{it}}.$$

To measure variable costs in the (imperfect) U.S. firm level data, De Loecker, Eeckhout, and Unger (2020) use Cost of Goods Sold (COGS). Other authors have used instead COGS+SGA (Cost of Goods Sold, plus Sales, General, and Administrative) expenses (see, for example, Traina (2018)). The elasticity of output with respect to variable inputs is estimated using the production function estimation technique as outlined in Appendix A of De Loecker, Eeckhout, and Unger (2020). They note that most of the rise in aggregate markups they identify is still present holding the elasticity term constant: that is, it comes from an increase in the ratio of sales to variable costs, rather than a change in the elasticity of output with respect to variable inputs. But once again, if firms earn some rents, and workers' compensation includes at least some of these rents, then some rents to labor will be included as part of measured labor costs. Since the Cost of Goods Sold (COGS) often includes some portion of the firm's labor costs (typically, the portion which is directly tied to production), a decline in rent-sharing with labor would show up under this measure as a decline in COGS relative to sales, and therefore would lead to a mechanical increase in the measured markup with no change in the underlying product market power of the firm.

Appendix G: Industry codes

G.1. Sector codes (NAICS and SIC)

For our calculations of the aggregate magnitude of labor rents, and the magnitude of labor rents by state, we use estimates of the industry wage premium at the *sector* level. At the aggregate level, NAICS level sector compensation data is available from the BEA for 1987-2016, and SIC level sector compensation data is available until 1997. At the state level, NAICS level sector compensation data is available from the BEA for 1997-2016, and SIC level until 1997. This means that we must estimate industry wage premia for both NAICS sectors and SIC sectors. It is relatively straightforward to estimate industry wage premia for SIC sectors in the CPS-ORG, because the CPS uses Census industry codes, which are based on SIC codes (we use the IPUMS-provided consistent code *ind1990*). It is less straightforward to crosswalk the industry codes in the CPS-ORG to the NAICS sectors. We first map the *ind1990* code, based on Census 1990 industry codes, into NAICS 3-digit codes (as described below), then aggregate this up into NAICS sectors.

G.2. Industry codes (BEA industry code, roughly NAICS-3 digit)

For our industry-level analyses, we use the same industry categorizations as Covarrubias, Gutiérrez, and Philippon (2019), whose industry classifications are primarily based on BEA industry codes. Data on value added, compensation, gross operating surplus, depreciation, investment, and fixed assets are available from the BEA at the level of these BEA industry codes from 1987-2016.

For our industry-level measures of labor rents, and wage premia, which are estimated from the CPS, we map the *ind1990* code (provided by IPUMS as a consistent industry code over time, based on Census 1990 industry codes) into NAICS 3-digit industry codes (as described in more detail below), then map these into BEA industry codes and group them as in Table F1 below (See also Table 10 in Covarrubias et al (2019)).

Mapping *ind1990* codes into NAICS 3-digit industry codes: We start with the Census NAICS industry crosswalk provided by the U.S. Census Bureau (available at https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html). This maps many of our *ind1990* codes into NAICS 3-digit industry codes directly. There are some *ind1990* industries which map into more than one NAICS code. For these, we start by

considering workers in the CPS IPUMS data in 2003 and later, who are assigned Census 2000 industry codes as well as the time-consistent *ind1990* code. Many of these Census 2000 industry codes *do* map directly into one NAICS code, and we use this accordingly. For workers in the data before 2003, we impute their NAICS code using the information from the workers post 2003: for each industry-occupation cell (*ind1990* by *occ1990*), we calculate the share of workers in 2003 and later who are mapped into each NAICS code. We then randomly assign workers pre-2003 in each of those industry-occupation cells to those NAICS codes, with the probability that they receive each NAICS code corresponding to the share of workers post-2003 in their same *ind1990-occ1990* cell who are mapped to that NAICS code. A small number of *ind1990* codes are not mapped: the biggest are Manufacturing, n.s., and Metal industries, n.s., which correspond to a number of different possible codes with no obvious way of allocating people between them.

Table F1: Mapping of BEA industry codes to our industry codes *(replicating Covarrubias et al 2019)*

BEA industry category	**Our industry category**
Agriculture, forestry, fishing, and hunting	
Farms	Agr_farm
Forestry, fishing, and related activities	Agr_forest
Mining	
Oil and gas extraction	Min_oil_and_gas
Mining, except oil and gas	Min_ex_oil
Support activities for mining	Min_support
Utilities	Utilities
Construction	Construction
Manufacturing	
Durable goods	
Wood products	Dur_wood
Nonmetallic mineral products	Dur_nonmetal
Primary metals	Dur_prim_metal
Fabricated metal products	Dur_fab_metal
Machinery	Dur_machinery
Computer and electronic products	Dur_computer
Electrical equipment, appliances, and components	Dur_electrical
Motor vehicles, bodies and trailers, and parts	Dur_transp
Other transportation equipment	Dur_transp
Furniture and related products	Dur_furniture
Miscellaneous manufacturing	Dur_misc
Nondurable goods	
Food and beverage and tobacco products	Nondur_food
Textile mills and textile product mills	Nondur_textile

Apparel and leather and allied products	Nondur_apparel
Paper products	Nondur_paper
Printing and related support activities	Nondur_printing
Petroleum and coal products	Nondur_petro
Chemical products	Nondur_chemical
Plastics and rubber products	Nondur_plastic
Wholesale trade	Wholesale_trade
Retail trade	Retail_trade
Transportation and warehousing	
Air transportation	Transp_air
Rail transportation	Transp_rail
Water transportation	Transp_water
Truck transportation	Transp_truck
Transit and ground passenger transportation	Transp_passenger
Pipeline transportation	Transp_pipeline
Other transportation and support activities	Transp_other
Warehousing and storage	Transp_storage
Information	
Publishing industries, except internet (includes software)	Inf_publish
Motion picture and sound recording industries	Inf_motion
Broadcasting and telecommunications	Inf_telecom
Data processing, internet publishing, and other information services	Inf_data
Finance, insurance, real estate, rental, and leasing	
Finance and insurance	
Federal Reserve banks, credit intermediation, and related activities	Finance_banks
Securities, commodity contracts, and investments	Finance_securities
Insurance carriers and related activities	Insurance
Funds, trusts, and other financial vehicles	Finance_funds
Real estate and rental and leasing	
Real estate	Omitted
Rental and leasing services and lessors of intangible assets	Rental_leasing
Professional, scientific, and technical services	
Legal services	Legal_serv
Computer systems design and related services	Computer_serv
Miscellaneous professional, scientific, and technical services	Misc_serv
Management of companies and enterprises	Omitted
Administrative and waste management services	
Administrative and support services	Adm_support
Waste management and remediation services	Waste_mgmt
Educational services	Educational
Health care and social assistance	
Ambulatory health care services	Health_ambulatory

Hospitals and nursing and residential care facilities	Health_hospitals
Social assistance	Health_social
Arts, entertainment, and recreation	
Performing arts, spectator sports, museums, and related activities	Arts_performing
Amusements, gambling, and recreation industries	Arts_recreation
Accommodation and food services	
Accommodation	Acc_accomodation
Food services and drinking places	Acc_food
Other services, except government	Other_ex_gov

Table F2: List of industries for which we have various variables available

Note that for all our industry-level analysis, we exclude financial industries, real estate, and the management of companies and enterprises, in keeping with our focus on the nonfinancial corporate sector in the baseline analysis.

Industry	Labor share	Imputed labor rents	Concentration (Compustat, import-adjusted)	Concentration (Census, import-adjusted)	Q
Acc_accomodation	X	X	X	X	X
Acc_food	X	X	X	X	X
Adm_support	X	X	X	X	X
Agr_farm	X	X			X
Agr_forest	X	X			X
Arts_performing	X	X		X	X
Arts_recreation	X		X	X	X
Computer_serv	X	X	X	X	X
Construction	X	X	X		X
Dur_computer	X	X	X	X	X
Dur_electrical	X	X	X	X	X
Dur_fab_metal	X	X	X	X	X
Dur_furniture	X	X	X	X	X
Dur_machinery	X	X	X	X	X
Dur_misc	X	X	X	X	X
Dur_nonmetal	X	X	X	X	X
Dur_prim_metal	X	X	X	X	X
Dur_transp	X	X	X	X	X
Dur_wood	X	X	X	X	X
Educational	X	X		X	X
Health_ambulatory	X	X		X	X
Health_hospitals	X	X	X	X	X
Health_social	X	X		X	
Inf_data	X	X	X	X	X

Inf_motion	X	X	X	X	X
Inf_publish	X	X	X	X	X
Inf_telecom	X	X	X	X	X
Legal_serv	X	X		X	X
Min_ex_oil	X	X	X		X
Min_oil_and_gas	X	X	X		X
Min_support	X		X		X
Misc_serv	X	X		X	X
Nondur_apparel	X	X	X	X	X
Nondur_chemical	X	X	X	X	X
Nondur_food	X	X	X	X	X
Nondur_paper	X	X	X	X	X
Nondur_petro	X	X	X	X	X
Nondur_plastic	X	X	X	X	X
Nondur_printing	X	X	X	X	X
Nondur_textile	X	X	X	X	X
Other_ex_gov	X	X		X	X
Retail_trade	X	X	X	X	X
Transp_air	X	X	X	X	X
Transp_other	X	X	X	X	X
Transp_passenger	X	X	X	X	X
Transp_pipeline	X	X	X	X	X
Transp_rail	X	X	X		X
Transp_storage	X	X		X	
Transp_truck	X	X	X	X	X
Transp_water	X	X	X	X	X
Utilities	X	X	X	X	X
Waste_mgmt	X	X	X	X	X
Wholesale_trade	X	X	X	X	X

Appendix References

This list contains sources referred to in the Appendix but not contained in the references list of the main paper.

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