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DISCUSSION PAPER SERIES

281/26

Wage Stagnation and Productivity Pass-Through: Evidence from Japanese Manufacturing

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Reference

JEL Codes: E24, J24, J31, J42

Keywords: Wage stagnation; productivity pass-through; wage decomposition; labor productivity

Recommended Citation: Ken Yamada (2026): Wage Stagnation and Productivity Pass-Through: Evidence from Japanese Manufacturing. RFBerlin Discussion Paper No. 281/26

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Wage Stagnation and Productivity Pass-Through: Evidence from Japanese Manufacturing*

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October 2026

Abstract

This paper examines productivity pass-through to wages in Japanese manufacturing over the 1980–2019 period. Productivity pass-through is positive and often sizable in earlier periods, declines over time, and becomes small across all six worker types defined by sex and age. Counterfactual accounting shows that this decline contributes more to wage stagnation than the slowdown in productivity growth. Pass-through is lower with higher capital intensity, employment concentration, and part-time employment. Among the observed changes in these characteristics, the implied reduction from the increase in capital intensity is the largest. Pass-through is generally larger for productivity changes with broader regional scope.

KEYWORDS: wage stagnation; productivity pass-through; wage decomposition; labor productivity

JEL CLASSIFICATION: E24, J24, J31, J42.

*I am grateful to Mitsuru Katagiri, Shinnosuke Kikuchi, Toshiaki Komatsu, Yuta Takahashi, Kazuhiro Teramoto, and seminar participants at Doshisha University, Hitotsubashi University, the Economic and Social Research Institute, and the Summer Workshop on Economic Theory for helpful comments. I gratefully acknowledge financial support from JSPS KAKENHI grant number 26K04947.

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1 Introduction

Real wage growth has slowed substantially across advanced economies in recent decades ([Machin, 2025](#)). Weak wage growth in Japan is often linked to slow productivity growth. Yet wages can stagnate even as productivity rises if the pass-through of productivity gains to wages weakens. This paper examines the evolution of productivity pass-through in Japanese manufacturing over four decades and quantifies the contribution of changes in productivity pass-through to wage stagnation, drawing on establishment-level data on value added available from 1980 to 2019.¹

Wage growth differs considerably across sex and age groups, whereas productivity growth differs across establishment types. Measuring productivity pass-through for different worker types requires a measure of the productivity environment faced by each type. Given that workers of different types are employed in different mixes of establishment types, I construct this environment for workers of each type in each region by aggregating productivity across establishment types using the employment shares of that worker type as weights. I then estimate productivity pass-through separately for six worker types defined by sex and age.

Productivity pass-through is positive and often sizable in earlier periods, but generally declines over time and becomes small across all six worker types in later periods. I decompose productivity pass-through into three components: pass-through into the unweighted mean of wage growth by job type, pass-through into changes in the relative wage structure across job types, and pass-through into employment reallocation across job types. The decline is concentrated primarily in the first component. Neither of the other two components declines consistently across worker types, even though employment shares across job types within worker types change substantially over the four decades.

The decline in productivity pass-through is quantitatively important for wage stagnation. I construct a counterfactual for wage growth that restores the earlier growth rate of the productivity environment and the earlier extent of productivity pass-through. The counterfactual accounting separates the difference between counterfactual and actual wages into the contributions of the slowdown in productivity growth and the decline in productivity pass-through. The contribution of the decline in productivity pass-through is larger than that of the slowdown in productivity growth for all six worker types and accounts for more than half of the difference between counterfactual and actual wages in 2019.

Productivity pass-through can be understood in a bilateral bargaining framework in which the bargained wage depends on the firm's incremental value from retaining the worker and the worker's post-separation value. In this framework, productivity pass-through can be expressed as a weighted average of the productivity elasticities of these two values. A decline in productivity pass-through can result from changes in either of the two productivity elasticities or their relative weight. It does not necessarily imply a decline in the worker's bargaining weight. The

¹Manufacturing activities closely correspond to the economic concept of production as the transformation of inputs into output.

framework also provides a way to interpret variation in productivity pass-through across production and labor-market environments and with the geographic scope of productivity changes. Empirically, for all six worker types, the estimates of productivity pass-through into unweighted mean wage growth are lower in production environments with higher capital intensity and in labor-market environments with higher employment concentration and a greater prevalence of part-time employment. I then quantify the changes in pass-through implied by the observed changes in these characteristics from 1980 to 2019. The implied reduction from the increase in capital intensity is the largest for all six worker types.

Productivity pass-through also differs with the geographic scope of productivity changes. At the prefecture level, I separate the productivity environment into a regional component and a prefectural component. The regional component captures productivity changes in the other prefectures of the same region, while the prefectural component captures the deviation of productivity changes in the prefecture from those in the other prefectures of the same region. The decline in productivity pass-through is also evident at the prefecture level: both the pass-through of the regional component and the pass-through of the prefectural component are smaller in the 2000–2019 period than in the 1980–1999 period for all six worker types. In the 1980–1999 period, the pass-through of the regional component exceeds the pass-through of the prefectural component for all six worker types. In the 2000–2019 period, the pass-through of the regional component remains larger for all three male age groups and for younger and prime-age women. In the bargaining framework, a larger pass-through of the regional component is consistent with a larger productivity elasticity of the worker’s post-separation value with respect to the regional component than to the prefectural component. These estimates indicate that productivity pass-through is generally larger for productivity changes with broader regional scope than for more localized prefectural changes.

The decline in productivity pass-through is also evident under alternative and extended specifications. The decline remains when I instrument the productivity environment with shift-share instruments and when I account for delayed wage adjustment. Weak pass-through in the later period is not confined to either productivity gains or productivity losses, nor to either production or non-production workers. When the productivity environment is decomposed into permanent and transitory components, the pass-through of the permanent component declines for all six worker types.

The remainder of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the data, the measurement, and the empirical framework. Section 4 documents the decline in productivity pass-through and quantifies its contribution to wage stagnation. Section 5 presents a bargaining framework for interpreting productivity pass-through. Section 6 examines how productivity pass-through varies across production and labor-market environments. Section 7 examines how productivity pass-through differs between regional and prefectural productivity changes. Section 8 examines whether the decline in productivity pass-through remains under alternative and extended specifications. Section 9 concludes.

2 Related Literature

This paper relates to two broad strands of the literature. The first strand studies the transmission of firm performance into workers' wages and the role of employers in wage determination. A large literature on rent sharing shows that wages depend on employer productivity, profitability, and economic rents. [Card et al. \(2014\)](#) provide evidence from matched worker-firm data that workers share in firm rents in Italy. [Card et al. \(2018\)](#) synthesize evidence on the role of firms in wage determination and labor-market inequality. [Bell et al. \(2024\)](#) are particularly relevant for the temporal dimension of this paper: they document a substantial decline in rent sharing in the United Kingdom after 2000 and present related evidence for Europe and the United States. [Friedrich et al. \(2026\)](#) distinguish permanent and temporary firm-specific productivity shocks and find stronger wage pass-through for permanent shocks in Sweden.

A bargaining framework is used in Section 5 to interpret the empirical estimates of productivity pass-through. [Kline \(2025\)](#) reviews the modern monopsony literature, in which wage responses to firm-side shocks depend on labor supply to the firm. In bargaining models, wages depend on the gains from continued employment and the values available after separation. The analysis of productivity pass-through based on the bargaining model is complementary to analyses based on monopsony and search models.

Several studies in this strand inform the analysis in Section 6, which examines how productivity pass-through varies across production and labor-market environments. [Arai \(2003\)](#) finds that wages are positively associated with firm profits and capital intensity in Sweden after controlling for worker and firm characteristics. This result suggests that capital intensity may be relevant to wage determination, but it does not determine whether productivity pass-through should increase or decrease with capital intensity. [Fukao et al. \(2022, 2023\)](#) examine how technological and labor-market environments shape rent sharing in Japan, including the roles of TFP growth, ICT capital intensity, and non-standard employment. [Benmelech et al. \(2022\)](#) document weaker pass-through of productivity into wages in more concentrated local labor markets in the United States. [Leduc and Liu \(2024\)](#) show in a business-cycle model calibrated and estimated using U.S. data that automation can dampen wage responses to productivity gains even when the worker's bargaining weight is fixed.

Other studies in this strand inform the analysis in Section 7, which examines how productivity pass-through varies with the geographic scope of productivity changes. [Carlsson et al. \(2016\)](#) show that wages respond more strongly to productivity shocks shared with other firms in the same sector than to firm-specific productivity shocks in Sweden. [Caldwell and Danieli \(2024\)](#) show that workers with broader outside options earn more in Germany.

The second strand studies the long-run relationship between wages and labor productivity. [Schwellnus et al. \(2017\)](#) document that median compensation growth has lagged labor productivity growth in many OECD countries and decompose the gap into changes in labor's share and the ratio of median to average compensation. [Greenspon et al. \(2021\)](#) distinguish divergence

in the levels of productivity and pay from changes in the relationship between their growth rates. They document substantial long-run divergence in the United States and Canada while finding that faster productivity growth remains associated with faster pay growth. A widening gap between wages and productivity therefore does not by itself establish that productivity pass-through has weakened.

Related studies of Japan consider several explanations for weak wage growth. [Sommer \(2009\)](#) studies sluggish wage growth relative to productivity and emphasizes labor-market duality, low productivity in the service sector, and pressures on labor's share of income. [Chun et al. \(2024\)](#) find that slower labor productivity growth accounts for much of the slowdown in real wage growth in Japan and Korea, while changes in labor's terms of trade account for much of the difference between real wage growth and productivity growth. [Morikawa \(2025\)](#) documents divergence between productivity and real wages at the aggregate level in Japan while finding a strong positive relationship at the firm level, and examines how reallocation contributes differently to aggregate productivity and wages.

Against this background, this paper connects the two strands by examining how the wages of workers of each type relate to the productivity environment they face over four decades. It first estimates how productivity pass-through changes over time. Building on this analysis, it complements [Bell et al. \(2024\)](#) by identifying the margin of wage adjustment at which the decline in productivity pass-through occurs, quantifying its contribution to wage stagnation relative to the slowdown in productivity growth, and examining how changes in production and labor-market environments relate to the decline in productivity pass-through. It further examines variation in productivity pass-through with the geographic scope and temporal persistence of productivity changes. The bargaining framework provides a way to interpret both the decline in productivity pass-through over time and its variation along these dimensions.

3 Data, Measurement, and Empirical Framework

3.1 Data sources and samples

The analysis combines worker-level wage data from the Basic Survey on Wage Structure (BSWS), conducted by the Ministry of Health, Labour and Welfare, with establishment-level production data from the Census of Manufacturing (CoM) and the Economic Census for Business Activity (ECBA), both conducted by the Ministry of Economy, Trade and Industry. Data from the BSWS are available for 1980, 1985, and annually from 1989 to 2019 and contain information on earnings, hours, worker characteristics, occupation, industry, establishment size, part-time status, and prefecture for workers in establishments with at least five regular employees. Data from the CoM and ECBA together are available annually from 1980 to 2019 and contain information on value added, employment, industry, establishment size, and location for establishments with at least four employees. They also consistently contain information on cap-

ital stock from 1980 to 2019 for establishments with 30 or more regularly employed workers. Variables are harmonized across surveys and over time to construct consistent worker types, job types, establishment types, and geographic units. The BSWS is used to construct wages, employment shares, hours worked, and the share of part-time employees, while the CoM and ECBA data are used to construct labor productivity, capital intensity, and employment concentration.

I construct an employment sample and a wage sample from the BSWS. Both samples are restricted to employees in manufacturing aged 16 to 74, for whom relevant variables are observed. The employment sample is used to construct employment shares across establishment types and average hours, while the wage sample is used to construct hourly wages and employment shares across job types. For the wage sample, I exclude extreme observations with monthly hours worked below 10 or above 350, hourly wages below one-half of prefectural minimum wages, and real hourly wages of 50,000 yen or more. Nominal hourly wages are calculated as the sum of monthly earnings, including overtime allowances, divided by the sum of monthly hours worked including overtime. They are deflated by the consumer price index with a base year of 2000. Annual bonuses are not included in hourly wages and are examined separately. I multiply the survey weight by an inverse-probability weight that adjusts for changes over time in the probability of being an employee conditional on observed characteristics.² The resulting weights are used to calculate average log wages, employment shares, and average hours worked.

Workers are classified into six worker types by sex and age group: men and women aged 16–29, 30–54, and 55–74. For the wage decomposition in Section 3.5, workers are further classified into 12 job types by occupation, broad industry, and establishment size. Occupation is divided into production and non-production work, with non-production work comprising managerial, clerical, and technical occupations. Industry is divided into three groups: consumption goods, material goods, and capital goods. Establishment size is divided into two groups: 30 or more employees and fewer than 30 employees.

I construct a production sample from the CoM and ECBA. Establishments are classified into 12 establishment types by industry and establishment size. Industries are divided into six groups: light manufacturing; chemicals; ceramics and primary metals; fabricated metal and machinery; electrical and electronics; and transportation machinery. Establishment size is divided into the same two groups as in the classification of job types. Thus, establishment types do not distinguish occupation and use six industry groups, whereas job types distinguish occupation and use three broad industry groups.

²I use the Labor Force Survey (LFS) to construct the inverse-probability weights. For each year, I estimate a logit model for whether an individual is an employee using sex, age group, marital status, and prefecture. I truncate the predicted probabilities at the 1st and 99th percentiles, construct inverse-probability weights as the share of employees divided by the predicted probability, and rescale the weights so that their mean among employees is one. I then average these weights for groups defined by prefecture, sex, and age group within each year and merge the resulting weights into the BSWS. All calculations using the LFS are weighted by the LFS sample weights.

For the main analysis, the 47 prefectures are aggregated into ten regions: Hokkaido and Tohoku, Kita-Kanto, Minami-Kanto, Hokuiku, Tosan, Tokai, Kinki, Chugoku, Shikoku, and Kyushu and Okinawa. Aggregating prefectures into regions serves two purposes. First, it helps maintain sufficiently large samples across worker types and job types throughout the 1980–2019 period. Second, it accommodates employment reallocation across prefectures within the same region and allows the productivity environment to reflect productivity changes shared across prefectures in that region. Regional units provide a useful basis for examining aggregate wage stagnation while retaining variation across regions. Prefectural units are also used in Section 7 to compare productivity pass-through associated with regional and prefectural productivity changes.

Labor productivity is measured as the logarithm of aggregate real value added per labor hour for each establishment type, region, and year. Nominal value added is deflated by industry-specific output deflators with a base year of 2000. Value added is defined according to the Census of Manufacturing and the Economic Census for Business Activity.³ Labor input is constructed by multiplying the numbers of male and female employees in the production sample by the corresponding average annual hours, including overtime, from the employment sample and then summing across sex. Average hours are calculated for each sex, establishment type, region, and year after excluding extreme observations with monthly hours worked below 10 or above 350.

3.2 Productivity environment

For each region, I construct the productivity environment faced by workers of each type by aggregating productivity across establishment types with the employment shares of workers of that type as weights. Let a_{jrt} denote log real value added per labor hour for establishments of type j , region r , and year t . Let $n_{g jrt}$ denote employment of workers of type g in establishments of type j , region r , and year t , as constructed from the employment sample. The employment share of workers of type g in establishments of type j in region r in year t is

$$s_{g jrt} = \frac{n_{g jrt}}{\sum_j n_{g jrt}}.$$

The productivity environment faced by workers of type g in region r in year t is

$$a_{g r t} = \sum_j s_{g j r t} a_{j r t},$$

³For establishments with 30 or more regularly employed workers, value added is calculated by subtracting intermediate inputs, taxes, and depreciation from shipments and other operating revenues plus changes in inventories of finished goods and work-in-process. For establishments with fewer than 30 regularly employed workers, value added is calculated by subtracting intermediate inputs and taxes from shipments and other operating revenues.

Within a region and year, differences in the productivity environment a_{grt} across worker types arise from differences in their employment shares s_{gjr} across establishment types. The productivity environment a_{grt} summarizes the productivity of the establishment types in which workers of type g are employed.

Across regions and over time, the productivity environment a_{grt} varies with both productivity a_{jrt} and employment shares s_{gjr} . With contemporaneous employment shares, changes in employment shares can mechanically alter the productivity environment a_{grt} even without changes in productivity within establishment types. I therefore calculate changes in the productivity environment by weighting productivity changes within establishment types using lagged employment shares: $a_{grt} - a_{gr,t-1} \approx \sum_j s_{gjr,t-1} (a_{jrt} - a_{jr,t-1})$.⁴ This calculation excludes the part of the change in the productivity environment that arises from changes in employment shares. For each estimation period, I use the value of that productivity environment in the first year as the initial value and construct a chained index by recursively updating subsequent values as follows:

$$a_{grt} \approx a_{gr,t-1} + \sum_j s_{gjr,t-1} (a_{jrt} - a_{jr,t-1}). \quad (1)$$

Hereafter, a_{grt} denotes the productivity environment constructed using equation (1).

Section 6 examines three characteristics of the production and labor-market environments: capital intensity, employment concentration, and the prevalence of part-time employment. I measure capital intensity as the logarithm of real capital stock excluding land per labor hour for each region, industry, and year. Capital stock is deflated using industry-specific output deflators. I measure employment concentration for each region, industry, and year using the Herfindahl–Hirschman index, calculated as the sum of squared establishment employment shares. For workers of each type in each region, I aggregate the two characteristics across industries using the employment shares of workers of that type in that region. As described in equation (1), changes in both characteristics within each region and industry are aggregated using lagged employment shares and accumulated over time. I measure the prevalence of part-time employment from the employment sample as the share of part-time employees for each region, job type, and year. For workers of each type in each region, I construct the prevalence of part-time employment by aggregating these shares across job types with the employment shares of workers of that type in each job type.

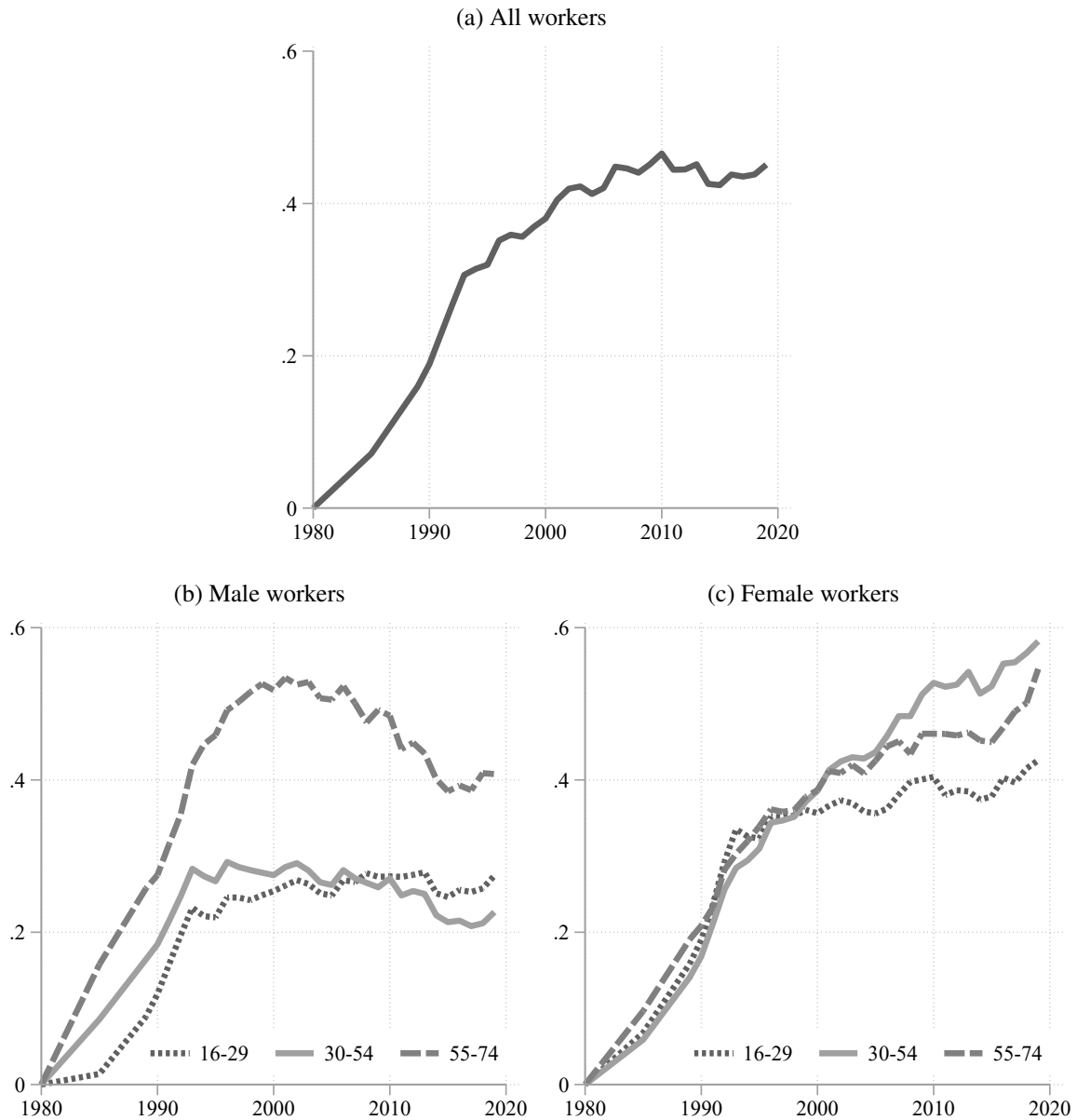
3.3 Evolution of wages and productivity

Figures 1 and 2 show the evolution of wages and labor productivity in Japanese manufacturing. Figure 1 reports average log real hourly wages for all workers and by worker type, defined by sex and age, while Figure 2 reports log real value added per labor hour for all workers and by

⁴The lagged employment shares for 1985 and 1989 are those in 1980 and 1985, respectively; from 1990 onward, they are those in the preceding year.

establishment type, defined by industry and establishment size.⁵

Figure 1: Evolution of average log real hourly wages

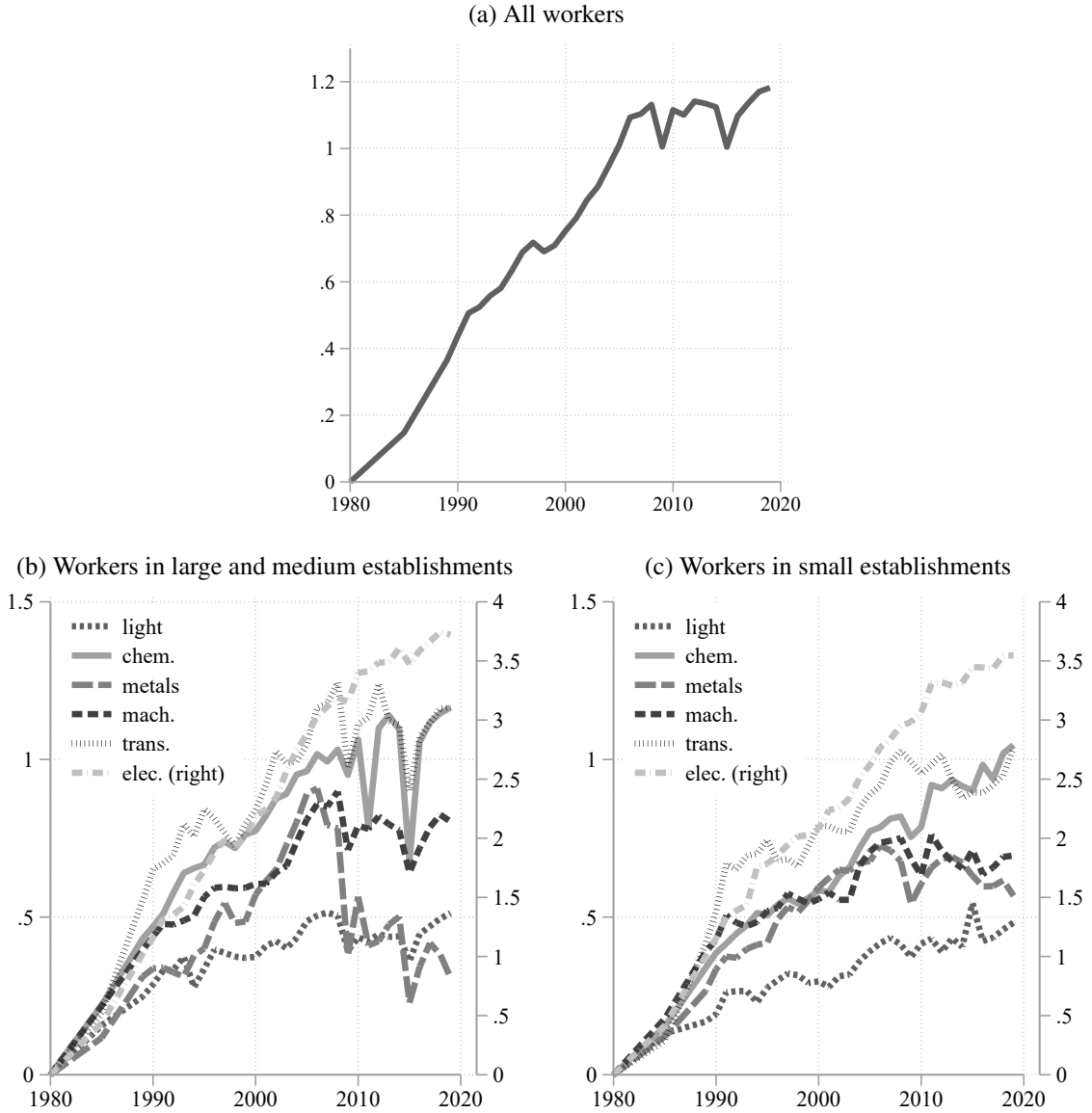


Notes: All series are deflated by the consumer price index, expressed in logarithms, and normalized to zero in 1980.

Figure 1 shows that average log wages for all workers rise substantially until the mid-1990s, after which wage growth slows markedly. Wage growth differs considerably across worker types. Wages for prime-age and older men rise until around 2000 but generally decline thereafter, whereas wages for prime-age and older women continue to trend upward through 2019. Figure 2 shows that aggregate productivity rises substantially over the 1980–2019 period, although productivity growth becomes weaker from the mid-2000s onward. Productivity

⁵Contemporaneous employment shares are used to construct the productivity series shown in Figure 2, whereas lagged employment shares are used to aggregate productivity changes across establishment types for the regression analysis, as described in equation (1).

Figure 2: Evolution of average log real value added per labor hour



Notes: All series are deflated by industry-specific output deflators, expressed in logarithms, and normalized to zero in 1980.

growth also differs considerably across establishment types defined by industry and establishment size. In particular, productivity rises much more strongly in electrical and electronics than in the other industries.

3.4 Empirical specification

For each worker type, I estimate a two-way fixed effects model that relates the wages of workers of type g to the productivity environment they face:

$$w_{grt} = \beta_g a_{grt} + \mu_{gr} + \lambda_{gt} + \gamma_{grt} + u_{grt}, \quad (2)$$

where w_{grt} is the average log real hourly wages of workers of type g in region r and year t , and a_{grt} is the productivity environment constructed using equation (1).⁶ The coefficient β_g captures the conditional relationship between the wages of workers of type g and the productivity environment they face. Because both variables are expressed in logarithms, β_g is an elasticity. I refer to this coefficient as productivity pass-through, or simply the pass-through coefficient.

The region fixed effects, μ_{gr} , absorb time-invariant differences across regions within each worker type, while the year fixed effects, λ_{gt} , absorb changes common across regions in a given year. Region-specific linear trends, γ_{grt} , absorb linear changes in wages that differ across regions within each worker type. I estimate equation (2) both without and with region-specific linear trends to assess whether the estimated productivity pass-through is sensitive to persistent region-specific trends in wages and the productivity environment. In both specifications, β_g is estimated from variation in wages and the productivity environment within regions, conditional on year fixed effects and, when included, region-specific linear trends.

Equation (2) is estimated over the 1980–2019 period and over five overlapping 20-year periods: the 1980–1999 period, the 1985–2004 period, the 1990–2009 period, the 1995–2014 period, and the 2000–2019 period. Moving the 20-year period forward in five-year increments allows productivity pass-through to be compared over time while keeping the length of the estimation period fixed. For each worker type, the estimation sample contains 330 region-year observations for the 1980–2019 period, 130 for the 1980–1999 period, 170 for the 1985–2004 period, and 200 for each of the 1990–2009, 1995–2014, and 2000–2019 periods. There are fewer observations in the earlier periods because the BSWs is unavailable for the 1981–1984 and 1986–1988 periods. The productivity environment a_{grt} is re-constructed separately for each estimation period as described in equation (1). In the specification with both contemporaneous and lagged productivity environments, the estimation sample contains 120 region-year observations in the 1980–1999 period and 200 for the 2000–2019 period. In the specification using the prefecture-level data, the estimation sample contains 611 prefecture-year observations for the 1980–1999 period and 940 for the 2000–2019 period.

Unless otherwise noted, standard errors are clustered at the region level to allow for heteroskedasticity and serial correlation within regions over time. Given the small number of regions, the clustered standard errors are corrected using the degrees-of-freedom adjustment of [Bell and McCaffrey \(2002\)](#), and p -values and confidence intervals are obtained using the wild bootstrap. In the specification using the prefecture-level data, standard errors are clustered at the prefecture level to allow for heteroskedasticity and serial correlation within prefectures over time.

⁶The results reported below are robust to the choice between the consumer price index and industry-specific output deflators.

3.5 Wage decomposition

The dependent variable in equation (2) is the average log real hourly wages of workers of each type in each region. Figures A1 and A2 show substantial differences across job types in both the levels and changes in wages and employment shares, respectively, within each worker type. Changes in average log wages can arise from the unweighted mean of wage growth by job type, changes in the relative wage structure across job types, or employment reallocation across job types. Intuitively, average log wages may increase because wages rise on average across job types, wages rise more in job types with larger employment shares, or employment shifts toward higher-wage job types. I decompose changes in average log wages into these three components and examine which of them accounts for the decline in productivity pass-through over time.

Let w_{ghrt} denote the average log real hourly wages of workers of type g in jobs of type h , region r , and year t , and let n_{ghrt} denote employment of workers of type g in jobs of type h , region r , and year t . Within each cell, w_{ghrt} is the weighted mean of log real hourly wages and n_{ghrt} is the sum of the weights defined in Section 3.1. The employment share of workers of type g in jobs of type h in region r in year t is

$$s_{ghrt} = \frac{n_{ghrt}}{\sum_h n_{ghrt}}.$$

Let H denote the number of job types, and define the unweighted averages across job types as $\bar{w}_{grt} = \sum_h w_{ghrt}/H$ and $\bar{s}_{grt} = \sum_h s_{ghrt}/H$. Define relative log wages and relative employment shares as deviations from these averages: $\tilde{w}_{ghrt} = w_{ghrt} - \bar{w}_{grt}$ and $\tilde{s}_{ghrt} = s_{ghrt} - \bar{s}_{grt}$. The decomposition is constructed separately for each estimation period. Let $\bar{\tilde{w}}_{ghr}$ and $\bar{\tilde{s}}_{ghr}$ denote the time averages of $\tilde{w}_{ghrt}$ and $\tilde{s}_{ghrt}$, respectively, over the relevant estimation period. Average log wages can then be written as

$$w_{grt} = \underbrace{\bar{w}_{grt}}_{\text{cell-wage}} + \underbrace{\sum_h \frac{1}{2} (\tilde{s}_{ghrt} + \bar{\tilde{s}}_{ghr}) (\tilde{w}_{ghrt} - \bar{\tilde{w}}_{ghr})}_{\text{relative-wage}} + \underbrace{\sum_h \frac{1}{2} (\bar{\tilde{w}}_{ghr} + \bar{\tilde{w}}_{ghr}) (\tilde{s}_{ghrt} - \bar{\tilde{s}}_{ghr})}_{\text{relative-share}} + \underbrace{\sum_h \bar{\tilde{w}}_{ghr} \bar{\tilde{s}}_{ghr}}_{\text{time-invariant}}. \quad (3)$$

The first term is the unweighted average across job types of the average log wages within each job type. Changes in this cell-wage component capture the unweighted mean of wage growth by job type. The second term is characterized by deviations of relative log wages from their time averages, while the third term is characterized by deviations of relative employment shares from their time averages. Changes in the relative-wage component capture changes in the relative wage structure across job types, while changes in the relative-share component capture employment reallocation across job types. The final term in equation (3) is constant

over time within each worker type and region and is therefore absorbed by the region fixed effects in equation (2). Appendix B.1 provides the derivation of equation (3).

I re-estimate equation (2) separately for the cell-wage, relative-wage, and relative-share components. In each case, I keep the rest of the specification and the estimation sample unchanged. Because the final term in equation (3) is absorbed by the region fixed effects, the three pass-through coefficients sum to the pass-through coefficient for average log wages.

4 Productivity Pass-Through

4.1 Decline in productivity pass-through

Table 1 reports estimates of productivity pass-through for three periods: 1980–2019, 1980–1999, and 2000–2019. For each period, estimates are reported both without and with region-specific trends. Productivity pass-through declines between the 1980–1999 period and the 2000–2019 period for all six worker types. With region-specific trends, productivity pass-through is positive for all six worker types and sizable for some worker types in the 1980–1999 period. In the 2000–2019 period, productivity pass-through is small in magnitude across all six worker types. The decline is statistically significant at the 10 percent level for all three male age groups and for older women. The estimates also decline for all six worker types when region-specific trends are excluded.

The decline in productivity pass-through is accompanied by a narrowing of the differences in pass-through estimates across worker types. In the 1980–1999 period, productivity pass-through varies considerably by sex and age. The estimates are relatively large for prime-age and older men and for older women. In the 2000–2019 period, the estimates are small across all six worker types.

The decline in productivity pass-through is distinct from the weakening of wage growth. Figure 1 shows that wage growth weakens substantially for prime-age and older men, whereas wages for prime-age and older women continue to rise. Productivity pass-through declines for all of these groups. Thus, a decline in productivity pass-through can occur even when average log wages continue to rise.

Figure 3 reports estimates of productivity pass-through for five overlapping 20-year periods. The estimates evolve differently across worker types in the first three periods: 1980–1999, 1985–2004, and 1990–2009. Productivity pass-through generally declines between the 1980–1999 and 1990–2009 periods and continues to decline from the 1990–2009 period to the 1995–2014 and 2000–2019 periods. The estimates are small across all six worker types in the last two periods: 1995–2014 and 2000–2019. The decline in productivity pass-through is observed not only when comparing the 1980–1999 and 2000–2019 periods reported in Table 1 but also when comparing the 1990–2009 period with the 1995–2014 and 2000–2019 periods, for which the number of observations is the same.

Table 1: Productivity pass-through across worker types and time periods

(a) Men						
	16–29		30–54		55–74	
1980–2019	0.034 (0.018)	0.037 (0.021)	0.106 (0.038)	0.066 (0.017)	0.073 (0.072)	0.060 (0.029)
1980–1999	0.170 (0.060)	0.192 (0.053)	0.240 (0.056)	0.275 (0.039)	0.407 (0.101)	0.365 (0.098)
2000–2019	0.017 (0.021)	0.024 (0.024)	0.034 (0.017)	0.042 (0.018)	–0.009 (0.040)	–0.022 (0.034)
Change	–0.153 (0.067) {0.047}	–0.168 (0.055) {0.000}	–0.205 (0.058) {0.018}	–0.233 (0.045) {0.018}	–0.416 (0.106) {0.015}	–0.387 (0.115) {0.017}
Trends	No	Yes	No	Yes	No	Yes

(b) Women						
	16–29		30–54		55–74	
1980–2019	0.012 (0.030)	0.047 (0.026)	–0.015 (0.027)	0.023 (0.034)	0.027 (0.049)	0.057 (0.045)
1980–1999	0.141 (0.055)	0.151 (0.057)	0.162 (0.046)	0.114 (0.105)	0.235 (0.052)	0.395 (0.072)
2000–2019	0.026 (0.025)	0.041 (0.033)	–0.012 (0.021)	0.018 (0.017)	–0.057 (0.024)	–0.058 (0.014)
Change	–0.116 (0.063) {0.088}	–0.110 (0.071) {0.214}	–0.174 (0.052) {0.009}	–0.096 (0.099) {0.324}	–0.292 (0.064) {0.004}	–0.452 (0.078) {0.002}
Trends	No	Yes	No	Yes	No	Yes

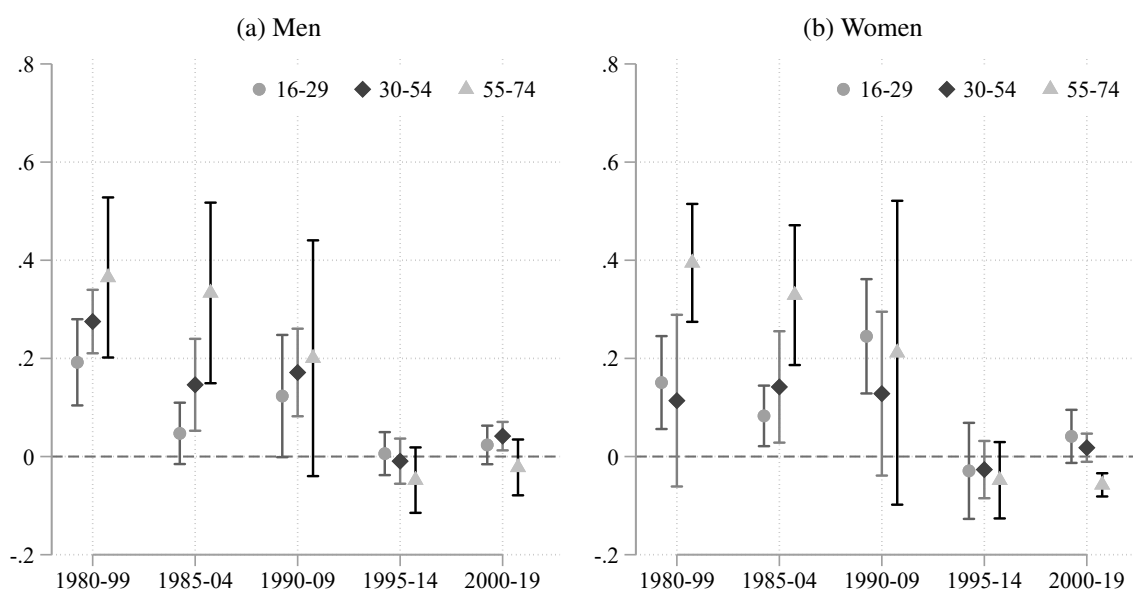
Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of [Bell and McCaffrey \(2002\)](#). Region and year fixed effects are included in all columns. Region-specific trends are included in even-numbered columns. “Change” is the 2000–2019 estimate minus the 1980–1999 estimate. The p -values in curly brackets are based on wild bootstrap tests of no change in pass-through coefficients, with 5,000 replications and clustering at the region level.

Appendix [C.1](#) examines the relationship between the bonus ratio and the productivity environment for each worker type. The decline in productivity pass-through into hourly wages is not offset by an increase in productivity pass-through into the bonus ratio. Appendix [C.2](#) examines the relationship between total employment and the productivity environment for each worker type. Unlike productivity pass-through to wages, this relationship does not decline across all six worker types.

4.2 Decomposition of productivity pass-through

Table [2](#) reports the pass-through coefficients for the cell-wage, relative-wage, and relative-share components defined in Section [3.5](#). The decomposition shows that the decline in productivity pass-through is concentrated primarily in pass-through into the cell-wage component. Neither pass-through into the relative-wage component nor pass-through into the relative-share component declines consistently across worker types. With region-specific trends, the pass-

Figure 3: Productivity pass-through over time



Notes: The figure reports pass-through coefficient estimates for five overlapping 20-year periods. Vertical bars denote 90 percent confidence intervals based on the wild bootstrap, with 5,000 replications and clustering at the region level. Region and year fixed effects and region-specific trends are included.

through coefficients for the cell-wage component are positive across all six worker types in the 1980–1999 period and become small in the 2000–2019 period. The pass-through coefficients for the cell-wage component also decline for all six worker types when region-specific trends are excluded.

With region-specific trends, the decline in the pass-through coefficient for the cell-wage component is larger than the decline in the pass-through coefficient for average log wages between the 1980–1999 period and the 2000–2019 period for all six worker types. Since the three pass-through coefficients sum to the pass-through coefficient for average log wages, changes in the pass-through coefficients for the relative-wage and relative-share components together offset part of the decline in the pass-through coefficient for the cell-wage component. With region-specific trends, the pass-through coefficients for the relative-wage component increase for all six worker types between the two periods. The pass-through coefficients for the relative-share component increase for some worker types and decrease for others. Thus, changes in pass-through into the relative-wage and relative-share components do not explain the decline in productivity pass-through across all six worker types. Appendix C.3 shows that the estimates of productivity pass-through into the cell-wage component are robust to adjustment for worker attributes within each worker type.

Table 2: Decomposition of productivity pass-through

(a) Men						
	16–29		30–54		55–74	
	1980–1999					
Cell-wage	0.137 (0.040)	0.177 (0.039)	0.214 (0.054)	0.285 (0.044)	0.337 (0.094)	0.395 (0.083)
Relative-wage	0.024 (0.024)	0.005 (0.029)	−0.015 (0.011)	−0.025 (0.015)	0.018 (0.034)	0.005 (0.034)
Relative-share	0.009 (0.010)	0.010 (0.012)	0.041 (0.017)	0.015 (0.008)	0.052 (0.039)	−0.035 (0.047)
	2000–2019					
Cell-wage	0.009 (0.022)	0.008 (0.021)	0.019 (0.019)	0.023 (0.019)	−0.040 (0.029)	−0.051 (0.030)
Relative-wage	0.004 (0.013)	0.006 (0.009)	0.015 (0.013)	0.015 (0.010)	0.019 (0.012)	0.013 (0.013)
Relative-share	0.005 (0.006)	0.009 (0.004)	0.000 (0.010)	0.003 (0.006)	0.012 (0.016)	0.015 (0.016)
Trends	No	Yes	No	Yes	No	Yes
(b) Women						
	16–29		30–54		55–74	
	1980–1999					
Cell-wage	0.145 (0.044)	0.172 (0.038)	0.158 (0.027)	0.158 (0.049)	0.189 (0.081)	0.436 (0.094)
Relative-wage	−0.003 (0.023)	−0.009 (0.031)	0.021 (0.013)	−0.017 (0.046)	−0.002 (0.077)	−0.089 (0.109)
Relative-share	−0.002 (0.017)	−0.012 (0.017)	−0.017 (0.030)	−0.027 (0.044)	0.048 (0.023)	0.047 (0.030)
	2000–2019					
Cell-wage	−0.009 (0.033)	−0.011 (0.032)	−0.003 (0.018)	0.013 (0.019)	−0.036 (0.028)	−0.045 (0.019)
Relative-wage	0.008 (0.020)	0.022 (0.024)	0.005 (0.015)	0.009 (0.013)	0.003 (0.015)	0.003 (0.017)
Relative-share	0.026 (0.017)	0.029 (0.022)	−0.015 (0.003)	−0.004 (0.009)	−0.024 (0.019)	−0.015 (0.026)
Trends	No	Yes	No	Yes	No	Yes

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of [Bell and McCaffrey \(2002\)](#). Region and year fixed effects are included in all columns. Region-specific trends are included in even-numbered columns.

4.3 Counterfactual wage growth

Weak wage growth can reflect both a slowdown in productivity growth and a decline in productivity pass-through. Figure 2 shows a slowdown in productivity growth, and Table 1 documents a decline in productivity pass-through across all six worker types. I assess the quantitative implications of these two changes for wage growth of each worker type by constructing counterfactual wage paths that restore the earlier growth rate of the productivity environment and

the earlier extent of productivity pass-through. I select 1993 as the base year because it is near the onset of prolonged stagnation in average log real hourly wages, as shown in Figure 1. I also use 2000 as an alternative base year because it is close to the midpoint of the sample period. Pass-through estimates from region-level aggregates are more closely aligned with the purpose of this accounting than those from firm- or establishment-level data because they capture the relationship between wage changes and productivity changes at a more aggregate level.

After the base year, I consider a counterfactual in which the productivity environment faced by workers of each type in each region continues to grow at the annual rate observed during the period between 1980 and the base year. For workers of type g in region r , let Δa_{grt}^1 denote the change in the productivity environment from the base year s to year t under this counterfactual, and let Δa_{grt}^2 denote the corresponding actual change. Thus, $\Delta a_{grt}^1 = [(a_{grs} - a_{gr,1980})/(s - 1980)](t - s)$ and $\Delta a_{grt}^2 = a_{grt} - a_{grs}$ for $t > s$. For this counterfactual accounting, I use a single productivity environment constructed over the 1980–2019 period using equation (1). Let β_g^1 and β_g^2 denote the pass-through estimates for the 1980–1999 period and the 2000–2019 period, respectively. Holding the other terms in equation (2) fixed, the changes in average log wages associated with changes in the productivity environment from the base year s to year t for workers of each type in each region are $\Delta w_{grt}^1 = \beta_g^1 \Delta a_{grt}^1$ and $\Delta w_{grt}^2 = \beta_g^2 \Delta a_{grt}^2$. The first corresponds to the case in which productivity continues to grow at its earlier rate and productivity pass-through remains at its earlier estimate. The second corresponds to the actual change in the productivity environment and the later pass-through estimate. The difference between these two wage changes measures how the change in average log wages from the base year s to year t would differ if productivity continued to grow at its earlier rate and productivity pass-through remained at its earlier estimate: $\Delta w_{grt}^1 - \Delta w_{grt}^2 = \beta_g^1 \Delta a_{grt}^1 - \beta_g^2 \Delta a_{grt}^2$. I construct the counterfactual wage path by adding this difference to the actual wage path. Let w_{grt}^{cf} denote the counterfactual average log wage. The difference between counterfactual and actual average log wages is then $w_{grt}^{cf} - w_{grt} = \Delta w_{grt}^1 - \Delta w_{grt}^2$. This difference can be decomposed in two equivalent ways, depending on whether the earlier or later pass-through estimate is used as the reference. I use the average of the two decompositions so that neither period serves as the sole reference. Define $\check{\beta}_g = (\beta_g^1 + \beta_g^2)/2$ and $\Delta \check{a}_{grt} = (\Delta a_{grt}^1 + \Delta a_{grt}^2)/2$. The difference between counterfactual and actual average log wages can then be written exactly

$$w_{grt}^{cf} - w_{grt} = \check{\beta}_g (\Delta a_{grt}^1 - \Delta a_{grt}^2) + \Delta \check{a}_{grt} (\beta_g^1 - \beta_g^2), \quad t > s. \quad (4)$$

The first term measures the contribution of the slowdown in productivity growth, using the average of the two pass-through estimates. The second term measures the contribution of the decline in productivity pass-through, using the average of the counterfactual and actual productivity changes. The two contributions sum exactly to the difference between the two wage paths. Appendix B.2 provides the derivation.

Table 3 reports the decomposition of the difference between counterfactual and actual

wages in 2019. Panels (a) and (b) report the results using base years of 1993 and 2000, respectively. I first construct the counterfactual wage difference for workers of each type in each region and then aggregate across regions using the observed employment weights. With region-specific trends, both the slowdown in productivity growth and the decline in productivity pass-through contribute positively to the difference for all six worker types in both panels. The contribution of the decline in productivity pass-through is larger than that of the slowdown in productivity growth for all six worker types in both panels.

Table 3: Decomposition of the difference between counterfactual and actual wages in 2019

(a) Base year: 1993						
	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
Total difference	0.253 {0.005}	0.311 {0.014}	0.398 {0.012}	0.190 {0.104}	0.131 {0.322}	0.393 {0.002}
Productivity slowdown	0.080 {0.010}	0.092 {0.007}	0.104 {0.014}	0.073 {0.012}	0.041 {0.243}	0.087 {0.002}
Pass-through decline	0.172 {0.000}	0.219 {0.013}	0.294 {0.019}	0.117 {0.206}	0.090 {0.343}	0.307 {0.002}
(b) Base year: 2000						
	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
Total difference	0.161 {0.005}	0.199 {0.014}	0.245 {0.014}	0.122 {0.098}	0.084 {0.322}	0.243 {0.002}
Productivity slowdown	0.052 {0.010}	0.057 {0.007}	0.060 {0.014}	0.047 {0.012}	0.025 {0.243}	0.049 {0.002}
Pass-through decline	0.110 {0.000}	0.142 {0.013}	0.185 {0.019}	0.074 {0.206}	0.058 {0.343}	0.194 {0.002}

Notes: The total difference and the two contributions are expressed in log points. The p -values in curly brackets are based on wild bootstrap tests of the null hypothesis that the corresponding quantity is zero, with 5,000 replications and clustering at the region level. Region and year fixed effects and region-specific trends are included.

The contribution of the decline in productivity pass-through varies considerably across worker types in both panels. The contribution increases with age among men and is larger for older than for younger workers among women for both base years. It is also larger for prime-age men than prime-age women. The contribution of the slowdown in productivity growth remains within a relatively narrow range across the six worker types.

The counterfactual accounting quantifies the importance of the decline documented in Table 1. The decline in productivity pass-through accounts for approximately 61 to 78 percent of the difference between counterfactual and actual wages in 2019 across the six worker types when the base year is 1993, and 61 to 80 percent when the base year is 2000.

5 A Conceptual Framework for Productivity Pass-Through

Section 4 shows that the decline in productivity pass-through is concentrated primarily in the cell-wage component, pointing to wage changes within job types as an important margin for understanding the decline. Counterfactual accounting highlights the quantitative importance of this decline for wage stagnation. This section introduces a bargaining framework to interpret productivity pass-through.

5.1 Bargaining model

Consider a standard bilateral Nash bargaining problem over the wage between a firm and a worker of type g (see, e.g., [Pissarides, 2000](#)). Let W_g denote the bargained wage, V_g^1 denote the firm's continuation value, before paying W_g , when the worker is retained, and V_g^0 denote the firm's continuation value after separation from the worker. Define $\Delta V_g \equiv V_g^1 - V_g^0$ as the firm's incremental value from retaining the worker (see, e.g., [Stole and Zwiebel, 1996](#)). Let $D_g > 0$ denote the worker's post-separation value. All payoffs in the bargaining problem are measured over the same horizon and in the same units.

Let $\theta_g \in (0, 1)$ denote the worker's bargaining weight in the Nash product. If the parties agree on a wage W_g , the worker's gain relative to separation is $W_g - D_g$, while the firm's gain is $\Delta V_g - W_g$. Suppose that the surplus from agreement is positive, so that $\Delta V_g > D_g > 0$. The Nash bargaining problem is

$$\max_{W_g \in [D_g, \Delta V_g]} (W_g - D_g)^{\theta_g} (\Delta V_g - W_g)^{1-\theta_g}.$$

The bargained wage is a weighted average of the worker's post-separation value and the firm's incremental value from retaining the worker:

$$W_g = (1 - \theta_g) D_g + \theta_g \Delta V_g.$$

Let $A > 0$ represent the productivity environment faced by the worker. Changes in this environment can affect both the firm's incremental value from retaining the worker and the worker's post-separation value. The empirical counterpart to the logarithm of A for workers of each type in each region is the productivity environment defined in Section 3.2. Define the firm-side productivity elasticity as $\varepsilon_g \equiv \partial \ln \Delta V_g / \partial \ln A$ and the worker-side productivity elasticity as $\eta_g \equiv \partial \ln D_g / \partial \ln A$. I assume $\varepsilon_g \geq 0$ and leave the sign of η_g unrestricted. The sign of η_g depends on how productivity gains affect the worker's post-separation value. A productivity gain concentrated at the worker's current employer may leave D_g largely unchanged, corresponding to $\eta_g \approx 0$. A productivity gain shared across relevant employers may raise D_g , corresponding to $\eta_g > 0$. A gain associated with labor-saving technological change or a decline in the value of transferable skills may instead reduce D_g , corresponding to $\eta_g < 0$.

Productivity pass-through can be expressed as the weighted average of the two elasticities:

$$\beta_g \equiv \frac{\partial \ln W_g}{\partial \ln A} = \omega_g \varepsilon_g + (1 - \omega_g) \eta_g, \quad (5)$$

where ω_g is the weight on the firm-side productivity elasticity:

$$\omega_g \equiv \frac{\theta_g \Delta V_g}{W_g} = \frac{\theta_g (\Delta V_g / D_g)}{(1 - \theta_g) + \theta_g (\Delta V_g / D_g)}.$$

Given $\Delta V_g > D_g > 0$, this weight satisfies $\theta_g < \omega_g < 1$. Here, θ_g is held fixed when the bargained wage is differentiated with respect to A . Productivity pass-through consequently lies between the two productivity elasticities: $\min\{\varepsilon_g, \eta_g\} \leq \beta_g \leq \max\{\varepsilon_g, \eta_g\}$. A lower β_g may reflect a lower ε_g , a lower η_g , or a change in ω_g that increases the weight on the smaller elasticity, and need not reflect a lower θ_g . Productivity pass-through can be negative if η_g is sufficiently negative, and can exceed one only if at least one of the two elasticities exceeds one. Thus, productivity pass-through is not restricted to the interval between zero and one.

Productivity pass-through can be close to zero in two distinct cases. First, suppose that $\eta_g \geq 0$. The two terms in equation (5) are both non-negative. Productivity pass-through can be close to zero only when both weighted terms are small. If ω_g is large, this can occur when ε_g is close to zero even if η_g is not small, because the weight on η_g is small. Conversely, if ω_g is small, this can occur when η_g is close to zero even if ε_g is not small, because the weight on ε_g is small. Second, suppose instead that $\eta_g < 0$. The two terms in equation (5) have opposite signs. A positive ε_g can be offset by a sufficiently negative η_g . Specifically, pass-through is approximately zero when

$$\eta_g \approx -\frac{\omega_g}{1 - \omega_g} \varepsilon_g = -\frac{\theta_g}{1 - \theta_g} \frac{\Delta V_g}{D_g} \varepsilon_g.$$

For a given positive ε_g , a larger θ_g or a larger ratio $\Delta V_g / D_g$ requires a larger absolute value of η_g for productivity pass-through to remain close to zero.

5.2 Interpretation of pass-through estimates

Section 4 documents three sets of results on productivity pass-through. The pass-through estimates vary across worker types, decline over time, and become small in magnitude across worker types in the 2000–2019 period. The first result, that productivity pass-through varies across worker types, can reflect differences across sex and age groups in the firm-side productivity elasticity, the worker-side productivity elasticity, and their relative weight. Productivity pass-through can be higher for a worker type if the response of the firm's incremental value from retaining the worker or the worker's post-separation value to productivity is stronger. It can also be higher if the bargained wage places relatively more weight on the value with the

larger productivity elasticity.

The second result, that productivity pass-through declines over time, can arise if productivity gains raise the firm's incremental value from retaining the worker by less than before, or if the worker's post-separation value becomes less responsive to productivity or even declines as productivity rises. Pass-through can also decline if the relative weight placed on the smaller productivity elasticity increases. The decline in productivity pass-through therefore need not reflect a decline in the worker's bargaining weight.

The third result, that productivity pass-through is small in magnitude in the 2000–2019 period, can be interpreted in terms of the two cases described in Section 5.1. Both terms in equation (5) are small, or a positive firm-side productivity elasticity is offset by a sufficiently negative worker-side productivity elasticity.

5.3 Sources of variation in productivity pass-through

Productivity pass-through depends on the firm-side and worker-side productivity elasticities and their relative weight, as shown in equation (5). The two elasticities and their relative weight may in turn vary across production and labor-market environments. Let z denote a characteristic of the production and labor-market environments. A change in z can affect how responsive the firm's incremental value from retaining the worker and the worker's post-separation value are to productivity changes. It can also alter the worker's bargaining weight or the relative levels of these two values, both of which affect the relative weight placed on the two productivity elasticities. The derivative of productivity pass-through with respect to z is

$$\begin{aligned} \psi_g \equiv \frac{\partial \beta_g}{\partial z} = & \omega_g \frac{\partial \varepsilon_g}{\partial z} + (1 - \omega_g) \frac{\partial \eta_g}{\partial z} \\ & + \omega_g (1 - \omega_g) (\varepsilon_g - \eta_g) \left[\frac{\partial \ln \Delta V_g}{\partial z} - \frac{\partial \ln D_g}{\partial z} + \frac{1}{\theta_g (1 - \theta_g)} \frac{\partial \theta_g}{\partial z} \right]. \end{aligned}$$

The first two terms capture changes in the productivity elasticities themselves. The final term captures a change in the relative weight placed on the two elasticities. An increase in $\Delta V_g/D_g$ or in θ_g raises the weight on ε_g . Holding the two productivity elasticities fixed, this raises productivity pass-through when $\varepsilon_g > \eta_g$ and lowers it when $\varepsilon_g < \eta_g$.

To see the role of the relative weight, suppose that z changes only the level of the worker's post-separation value D_g , without changing either productivity elasticity or the worker's bargaining weight. The expression above reduces to $\psi_g = -\omega_g (1 - \omega_g) (\varepsilon_g - \eta_g) (\partial \ln D_g / \partial z)$. When $\varepsilon_g > \eta_g$, ψ_g and $\partial \ln D_g / \partial z$ have opposite signs. A negative ψ_g then corresponds to D_g increasing with z , while a positive ψ_g corresponds to D_g decreasing with z .

More generally, a characteristic of the production and labor-market environments can affect the two productivity elasticities and their relative weight at the same time. The changes can reinforce or offset one another. Consequently, the sign of ψ_g is ambiguous. Section 6 ex-

amines how productivity pass-through varies with observable characteristics of the production and labor-market environments.

6 Productivity Pass-Through across Production and Labor-Market Environments

The bargaining framework in Section 5 suggests that productivity pass-through may vary across production and labor-market environments. This section first examines how productivity pass-through into the cell-wage component varies with capital intensity, employment concentration, and the prevalence of part-time employment over the 1980–2019 period. It then quantifies the changes in pass-through implied by the observed changes in these characteristics to assess their quantitative relevance to the decline in pass-through between 1980 and 2019.

Let z_{grt} denote one of the production or labor-market characteristics faced by workers of type g in region r and year t . For each worker type, I estimate the two-way fixed effects model:

$$\bar{w}_{grt} = \beta_g a_{grt}^c + \delta_g z_{grt}^c + \psi_g a_{grt}^c z_{grt}^c + \mu_{gr} + \lambda_{gt} + \gamma_{grt} + u_{grt}. \quad (6)$$

Here, $\bar{w}_{grt}$ is the cell-wage component defined in equation (3). A superscript c denotes deviation from the mean for the corresponding worker type over the 1980–2019 period. Thus, a_{grt}^c is the centered value of the productivity environment a_{grt} , and z_{grt}^c is the centered value of the corresponding production or labor-market characteristic. The coefficient β_g measures productivity pass-through into the cell-wage component when z_{grt} is at the mean for that worker type, while δ_g measures the slope of $\bar{w}_{grt}$ with respect to z_{grt} when the productivity environment is at the mean for that worker type. The coefficient ψ_g measures how this pass-through varies with z_{grt} and provides the empirical counterpart to ψ_g defined in Section 5.3.

Table 4 reports estimates of the coefficients in equation (6). Table 5 reports the implied changes in pass-through into the cell-wage component by multiplying the estimate of ψ_g by the change in the corresponding characteristic between 1980 and 2019. This calculation gives the change in pass-through into the cell-wage component implied by the observed change in each characteristic. Appendix C.4 shows that the estimates of ψ_g are robust to replacing contemporaneous production and labor-market characteristics with their lagged values.

6.1 Capital intensity

Panel (a) of Table 4 reports the estimates of the coefficients in equation (6) when z_{grt} is capital intensity. The estimates of ψ_g are negative for all six worker types, indicating that productivity pass-through into the cell-wage component is lower at higher levels of capital intensity. The estimates also decrease with age within both sexes. The estimates of δ_g vary in sign across worker types.

Table 4: Productivity pass-through into the cell-wage component across production and labor-market environments

(a) Capital intensity						
	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
a_{grt}^c	0.048 (0.028)	0.049 (0.030)	0.067 (0.070)	0.090 (0.030)	0.010 (0.019)	0.077 (0.075)
z_{grt}^c	–0.007 (0.021)	0.034 (0.016)	0.009 (0.032)	–0.047 (0.023)	0.036 (0.011)	0.011 (0.058)
$a_{grt}^c \times z_{grt}^c$	–0.059 (0.009)	–0.073 (0.018)	–0.122 (0.036)	–0.047 (0.023)	–0.070 (0.010)	–0.098 (0.047)
(b) Employment concentration						
	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
a_{grt}^c	0.030 (0.016)	0.060 (0.016)	0.017 (0.020)	0.019 (0.032)	0.027 (0.028)	0.059 (0.031)
z_{grt}^c	–1.810 (0.857)	–1.650 (1.424)	6.142 (3.988)	–4.469 (3.477)	–5.607 (3.886)	–12.074 (11.672)
$a_{grt}^c \times z_{grt}^c$	–7.173 (1.466)	–7.420 (2.173)	–2.315 (3.867)	–10.762 (4.707)	–15.456 (10.528)	–17.713 (16.965)
(c) Part-time employment						
	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
a_{grt}^c	0.034 (0.024)	0.065 (0.024)	0.027 (0.024)	0.034 (0.030)	0.054 (0.023)	0.077 (0.040)
z_{grt}^c	–0.107 (0.062)	–0.031 (0.124)	–0.080 (0.140)	–0.113 (0.074)	–0.190 (0.077)	–0.097 (0.075)
$a_{grt}^c \times z_{grt}^c$	–0.293 (0.147)	–0.307 (0.197)	–0.015 (0.217)	–0.383 (0.196)	–0.699 (0.159)	–0.511 (0.330)

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of [Bell and McCaffrey \(2002\)](#). Region and year fixed effects and region-specific trends are included. The variables a_{grt} and z_{grt} are centered at their respective means for the corresponding worker type, and z_{grt} is log capital intensity in panel (a), employment concentration in panel (b), and the part-time employment share in panel (c).

In a more capital-intensive production environment, the firm may depend less on retaining a particular worker. Productivity gains may then have more similar effects on firm value with and without the worker, making the firm’s incremental value from retaining the worker less responsive to productivity. In the model, this corresponds to a lower firm-side productivity elasticity ε_g . Capital deepening may also lower the worker-side productivity elasticity η_g if productivity gains become more labor-saving or reduce the value of transferable skills, making the worker’s post-separation value less responsive to productivity. A lower ε_g or a lower η_g reduces pass-through, and both elasticities can decline together.

Table 5 reports increases in capital intensity for all six worker types between 1980 and 2019. The increase is larger for younger workers and smaller for older workers, whereas the estimates

of ψ_g decrease with age. The implied change in pass-through into the cell-wage component is negative for all six worker types. The implied reduction increases with age within both men and women. Among the three characteristics, the implied reduction from the observed increase in capital intensity is the largest for all six worker types. For comparison, the implied reduction is about half as large as the decline in pass-through into the cell-wage component documented in Section 4 for younger men and women and is comparable in magnitude to the decline for prime-age women. For prime-age men and older workers, the implied reduction is smaller than the decline.

Table 5: Implied changes in pass-through into the cell-wage component

	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
Capital intensity	–0.104 (0.015)	–0.119 (0.030)	–0.167 (0.049)	–0.089 (0.043)	–0.124 (0.017)	–0.130 (0.062)
Δ (percent)	483.6	409.0	293.6	561.1	479.9	279.2
Employment concentration	0.005 (0.001)	0.006 (0.002)	0.003 (0.005)	0.001 (0.000)	–0.007 (0.005)	0.000 (0.000)
Δ (HHI points)	–7.4	–7.8	–12.6	–0.8	4.3	0.2
Part-time employment	–0.016 (0.008)	–0.017 (0.011)	–0.001 (0.012)	–0.033 (0.017)	–0.045 (0.010)	–0.047 (0.030)
Δ (percentage points)	5.6	5.5	5.3	8.7	6.4	9.1

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of Bell and McCaffrey (2002). Region and year fixed effects and region-specific trends are included. Each implied change is calculated using the estimate of ψ_g from the corresponding panel of Table 4 and the change from 1980 to 2019 in the corresponding regressor, in the units used in estimation. For each worker type, the change from 1980 to 2019 is calculated as the difference between the means across regions in the two years. For presentation, changes in capital intensity are converted from log changes to percent changes, changes in employment concentration are reported in HHI points, defined as the HHI multiplied by 10,000, and changes in the part-time share are reported in percentage points.

6.2 Employment concentration

Panel (b) of Table 4 reports the estimates of the coefficients in equation (6) when z_{grt} is employment concentration. The estimates of ψ_g are negative for all six worker types, indicating that productivity pass-through into the cell-wage component is lower at higher levels of employment concentration. The estimates are larger in magnitude for women than for men within each age group. Among men, the estimates are similar for younger and prime-age workers and substantially smaller in magnitude for older workers, whereas among women they decrease with age. The estimates of δ_g are negative for all worker types except older men.

Higher employment concentration means that a larger share of employment is located in a smaller number of establishments. When employment is more concentrated, productivity gains may be less likely to translate into improved employment opportunities outside the worker’s current establishment, weakening the response of the worker’s post-separation value to productivity. In the model, this corresponds to a lower worker-side productivity elasticity, which can reduce productivity pass-through.

Table 5 reports decreases in employment concentration between 1980 and 2019 for all three male worker types. The decrease is the largest for older men. Because the estimates of ψ_g are negative, these changes imply increases in pass-through into the cell-wage component for all three groups. Among women, concentration falls slightly for younger women, increases for prime-age women, and changes little for older women. The corresponding implied changes are a small increase for younger women, a small decline for prime-age women, and essentially no change for older women. All of these implied changes are small relative to the decline in pass-through into the cell-wage component documented in Section 4, reflecting the absence of a substantial increase in employment concentration between 1980 and 2019. For men, the implied changes are opposite in sign to the decline documented in Section 4.

6.3 Part-time employment

Panel (c) of Table 4 reports the estimates of the coefficients in equation (6) when z_{grt} is the part-time employment share. The estimates of ψ_g are negative for all six worker types, indicating that productivity pass-through into the cell-wage component is lower when the prevalence of part-time employment is higher. The estimates are larger in magnitude for women than for men within each age group. Among women, the estimate is largest in magnitude for prime-age workers, while among men the estimate for older workers is close to zero. The estimates of δ_g are also negative for all six worker types.

Greater reliance on part-time employment can make it easier for the firm to adjust employment, reducing its dependence on retaining a particular worker when productivity gains occur. In the model, this can make the firm's incremental value from retaining the worker less responsive to productivity, lowering the firm-side productivity elasticity. Greater reliance on part-time employment can also make employment opportunities available to the worker after separation less responsive to productivity gains, lowering the worker-side productivity elasticity. A lower firm-side or worker-side productivity elasticity reduces productivity pass-through.

Table 5 reports increases in the prevalence of part-time employment between 1980 and 2019 for all six worker types. The increase is larger for women than for men within each age group. Among men, the implied reductions are similar for younger and prime-age workers and close to zero for older workers. Among women, the implied reductions are larger than for men in each age group and are largest for older women. The observed increase in part-time employment corresponds to an implied reduction in pass-through for all six worker types. This pattern differs from that for employment concentration, for which the implied changes vary in sign across worker types. For all six worker types, the implied reduction from the observed increase in part-time employment is smaller in magnitude than the implied reduction from the observed increase in capital intensity.

7 Geographic Scope of Productivity Changes

The bargaining framework in Section 5 suggests that productivity pass-through may vary with the geographic scope of productivity changes. This section examines whether wages respond differently to productivity changes extending to other prefectures in the same region than to productivity changes localized within a prefecture.

7.1 Regional and prefectural changes

I compare pass-through associated with productivity changes in the other prefectures of the same region with pass-through associated with the deviation of productivity changes in the prefecture from those in the other prefectures of the same region. To do so, I re-construct wages and the productivity environment at the prefecture level. Let a_{gpt} denote the productivity environment faced by workers of type g in prefecture p , constructed using the same procedure as in equation (1). For each estimation period, I normalize a_{gpt} and the regional component a_{gpt}^R defined below to zero in the first year t_0 and construct subsequent values by accumulating productivity changes using lagged employment shares. This normalization does not affect the estimated pass-through coefficients. Labor input in each prefecture is calculated using the average hours by sex, industry, establishment size, region, and year described in Section 3.1.

I construct the regional component using productivity changes in the other prefectures of the same region. For each prefecture p and establishment type j , let a_{jrt}^{-p} denote log labor productivity calculated from establishments located in the other prefectures of region r , where r is the region containing prefecture p . Value added and labor input are first aggregated across these other prefectures, and labor productivity is then calculated from the two aggregates. Equivalently, I subtract the value added and labor input of prefecture p from the corresponding regional totals before calculating log labor productivity. This produces a leave-one-out measure of productivity for each prefecture and establishment type.

Let $s_{gjp,t}$ denote the employment share of establishment type j for workers of type g in prefecture p and year t . The regional component is constructed using lagged employment shares:

$$a_{gpt}^R \approx a_{gp,t-1}^R + \sum_j s_{gjp,t-1} \left(a_{jrt}^{-p} - a_{jr,t-1}^{-p} \right).$$

The productivity changes entering a_{gpt}^R are measured in the other prefectures of the same region, while the weights used to aggregate them across establishment types are the lagged employment shares of workers of that type in prefecture p . I define the prefectural component as the part of the productivity environment in prefecture p that remains after removing the regional component: $a_{gpt}^P = a_{gpt} - a_{gpt}^R$.

For each worker type, I estimate the pass-through of the two components jointly:

$$w_{gpt} = \beta_g^R a_{gpt}^R + \beta_g^P a_{gpt}^P + \mu_{gp} + \lambda_{gt} + \gamma_{gpt} + u_{gpt}. \quad (7)$$

The coefficient β_g^R measures pass-through associated with productivity changes in the other prefectures of the same region, conditional on the prefectural component. The coefficient β_g^P measures pass-through associated with the deviation of productivity changes in the prefecture from those in the other prefectures of the same region, conditional on the regional component.

Table 6 reports the pass-through estimates for the 1980–1999 period and the 2000–2019 period. In the 1980–1999 period, the pass-through coefficient on the regional component exceeds that on the prefectural component for all six worker types. The difference is statistically significant at the 10 percent level for prime-age and older men and for younger and older women. For younger men and prime-age women, the pass-through coefficient on the regional component is also larger, although the differences are not statistically significant.

Table 6: Pass-through of regional and prefectural productivity changes

	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
	1980–1999			1980–1999		
Regional	0.103 (0.058)	0.258 (0.034)	0.251 (0.082)	0.081 (0.043)	0.089 (0.052)	0.253 (0.071)
Prefectural	0.011 (0.045)	0.079 (0.026)	0.115 (0.060)	0.003 (0.029)	0.052 (0.029)	0.086 (0.062)
Difference	0.092 (0.055) {0.120}	0.179 (0.023) {0.000}	0.136 (0.074) {0.081}	0.078 (0.040) {0.066}	0.038 (0.045) {0.424}	0.167 (0.078) {0.043}
	2000–2019			2000–2019		
Regional	0.018 (0.026)	0.067 (0.026)	−0.018 (0.050)	0.036 (0.028)	0.052 (0.042)	−0.053 (0.034)
Prefectural	−0.010 (0.014)	−0.004 (0.014)	−0.025 (0.026)	0.000 (0.014)	−0.002 (0.025)	−0.028 (0.024)
Difference	0.028 (0.017) {0.130}	0.071 (0.020) {0.001}	0.006 (0.042) {0.887}	0.036 (0.024) {0.158}	0.054 (0.026) {0.039}	−0.025 (0.018) {0.147}

Notes: Standard errors in parentheses are clustered at the prefecture level and corrected using the degrees-of-freedom adjustment of Bell and McCaffrey (2002). “Regional” denotes the regional component constructed from productivity in the other prefectures of the same region. “Prefectural” denotes the remaining prefectural component defined in Section 7.1. Prefecture and year fixed effects and prefecture-specific trends are included. “Difference” is the pass-through coefficient on the regional component minus the pass-through coefficient on the prefectural component. The p -values in curly brackets are based on wild bootstrap tests of equality between the two pass-through coefficients, with 5,000 replications and clustering at the prefecture level.

Both pass-through coefficients are smaller in the 2000–2019 period than in the 1980–1999 period for all six worker types. In the later period, the pass-through coefficient on the regional component is larger than the pass-through coefficient on the prefectural component for all three male age groups and for younger and prime-age women, and smaller for older women. Equality of the two pass-through coefficients is rejected for prime-age men and prime-age women.

7.2 Geographic scope and worker's post-separation value

The geographic scope of productivity changes can affect the worker's post-separation value even when the firm's incremental value has the same productivity elasticity with respect to the regional and prefectural components. Let ε_g^R and ε_g^P denote the productivity elasticities of the firm's incremental value with respect to the regional and prefectural components. Let η_g^R and η_g^P denote the productivity elasticities of the worker's post-separation value with respect to the regional and prefectural components. For the interpretation below, suppose that $\varepsilon_g^R = \varepsilon_g^P$. Equation (5) then implies

$$\beta_g^R - \beta_g^P = (1 - \omega_g) (\eta_g^R - \eta_g^P). \quad (8)$$

Because $0 < \omega_g < 1$, $\beta_g^R > \beta_g^P$ implies $\eta_g^R > \eta_g^P$. One economic reason for this is that productivity changes shared across employers in the other prefectures of the same region may affect the worker's post-separation value through employment opportunities available after separation, whereas more localized productivity changes affect a narrower set of potential employers.

Under $\varepsilon_g^R = \varepsilon_g^P$, the estimates in Table 6 imply a larger productivity elasticity of the worker's post-separation value with respect to productivity changes of broader regional scope than to more localized prefectural changes for all six worker types in the earlier period and for five of the six in the later period. If $\varepsilon_g^R \neq \varepsilon_g^P$, the difference in the pass-through coefficients can also reflect differences in how the firm's incremental value from retaining the worker responds to the regional and prefectural components.

8 Extensions and Robustness

The preceding sections document a decline in productivity pass-through across all six worker types and examine how productivity pass-through varies across production and labor-market environments and with the geographic scope of productivity changes. This section examines whether the decline remains under alternative and extended specifications. I first instrument the productivity environment using shift-share instruments based on leave-one-out national productivity changes and lagged employment shares. I then distinguish productivity gains from losses, allow wages to depend on contemporaneous and lagged productivity environments, estimate productivity pass-through separately for production and non-production workers, and decompose productivity into permanent and transitory components.

8.1 Instrumented changes

Productivity changes within a region may reflect region-specific shocks that also affect wages. To address this concern, I use shift-share instruments that combine leave-one-out national productivity changes by establishment type with regional variation in lagged employment shares of a given worker type across establishment types. The productivity changes used to construct

the instruments capture changes outside a given region for each establishment type, while the lagged employment shares capture variation across regions in the preexisting exposure of a given worker type to those establishment types.

For each establishment type, I calculate the average productivity change across all regions other than region r , weighting each region by lagged total employment in that establishment type. For workers of type g in region r , I aggregate these productivity changes within each of three broad groups of manufacturing industries using the lagged employment shares of workers of that type in that region. As described in equation (1), I accumulate these changes over time to construct three instruments, one for each of three broad groups of manufacturing industries, to preserve differences in leave-one-out productivity changes across the groups. The three groups are light manufacturing; chemicals, ceramics, and primary metals; and fabricated metal and machinery, electrical and electronics, and transportation machinery. The three instruments are used jointly as instruments for the productivity environment a_{grt} , under the assumption that they affect wages in region r only through a_{grt} , conditional on region and year fixed effects and region-specific trends. I otherwise retain the specification in equation (2) and estimate it by two-stage least squares. I also report 90 percent confidence sets based on the conditional likelihood-ratio test of [Moreira \(2003\)](#), which is robust to weak instruments.

Table 7 reports productivity pass-through estimates using the shift-share instruments for the 1980–1999 and 2000–2019 periods. Productivity pass-through declines between the two periods for all six worker types, as in Table 1. The changes are statistically significant at the 10 percent level for prime-age men and older women. With region-specific trends, the pass-through estimates are positive for all six worker types in the 1980–1999 period. In the 2000–2019 period, the estimates are generally much smaller than in the earlier period, although some estimates remain statistically distinguishable from zero. In particular, the estimate for prime-age men is positive and statistically significant. The 90 percent confidence sets based on conditional likelihood-ratio tests also exclude zero for prime-age men and younger women.

The estimates using these instruments are generally larger than the corresponding estimates with region-specific trends in Table 1 in the 1980–1999 period, particularly for younger and prime-age men and younger women, whereas pass-through estimates are small in both specifications in the 2000–2019 period. Thus, the decline in productivity pass-through remains when the productivity environment is instrumented using the shift-share instruments. This result suggests that the decline documented in Section 4 is not driven solely by region-specific shocks that affect both productivity changes within the region and wages.

8.2 Positive and negative changes

The decline in productivity pass-through could partly reflect changes in the composition of productivity gains and losses. If pass-through is stronger for gains than for losses, a shift from gains toward losses can reduce the estimated pass-through coefficient even if the pass-

Table 7: Pass-through of instrumented productivity changes

(a) Men			
	16–29	30–54	55–74
1980–1999	0.336	0.386	0.345
	(0.146)	(0.057)	(0.145)
	[−0.218, −0.203]	[−0.075, 0.001]	[0.011, 0.408]
	∪ [0.311, 8.799]	∪ [0.325, 0.428]	
	<i>4.07</i>	<i>13.70</i>	<i>28.83</i>
2000–2019	0.089	0.057	−0.008
	(0.051)	(0.027)	(0.071)
	[−0.013, 0.410]	[−0.537, −0.124]	[−0.185, 0.723]
		∪ [0.036, 0.126]	
	<i>19.61</i>	<i>10.33</i>	<i>3.27</i>
Change	−0.247	−0.328	−0.353
	{0.190}	{0.005}	{0.235}
(b) Women			
	16–29	30–54	55–74
1980–1999	0.290	0.135	0.373
	(0.167)	(0.158)	(0.116)
	[−0.904, −0.888]	[0.099, 0.435]	[0.184, 0.354]
	∪ [0.098, 0.897]		
	<i>15.00</i>	<i>12.47</i>	<i>50.45</i>
2000–2019	0.054	0.004	−0.015
	(0.081)	(0.016)	(0.030)
	[0.056, 0.191]	[−0.019, 0.040]	[−0.046, 0.029]
	<i>25.50</i>	<i>19.71</i>	<i>23.44</i>
Change	−0.236	−0.131	−0.388
	{0.382}	{0.472}	{0.069}

Notes: Standard errors in parentheses are clustered at the region level. The p -values in curly brackets are based on wild bootstrap tests of no change in the corresponding coefficients, with 5,000 replications and clustering at the region level. The 90 percent confidence sets reported in square brackets are based on conditional likelihood-ratio tests. First-stage F statistics for the joint significance of the instruments are reported in italics. Region and year fixed effects and region-specific trends are included. “Change” is the 2000–2019 estimate minus the 1980–1999 estimate.

through coefficients for gains and losses do not change over time. I therefore examine whether productivity pass-through differs between productivity gains and losses. For each establishment type, I separate changes in log productivity into their positive and negative parts and aggregate them using the same procedure as in equation (1). For workers of each type in each region, I define cumulative productivity gains a_{grt}^+ and cumulative productivity losses a_{grt}^- from the first year t_0 of the estimation period as

$$a_{grt}^+ = \sum_{\tau=t_0+1}^t \sum_j s_{gjr,\tau-1} \max \{a_{jr\tau} - a_{jr,\tau-1}, 0\},$$

$$a_{grt}^- = \sum_{\tau=t_0+1}^t \sum_j s_{gjr,\tau-1} \min \{a_{jr\tau} - a_{jr,\tau-1}, 0\}.$$

Their sum equals the cumulative change in the productivity environment from the first year of the estimation period. The decomposition therefore preserves the productivity changes used to construct the productivity environment in equation (1) while allowing productivity pass-through to differ between positive and negative productivity changes.

For each worker type, I estimate the pass-through of the positive and negative components jointly:

$$w_{grt} = \beta_g^+ a_{grt}^+ + \beta_g^- a_{grt}^- + \mu_{gr} + \lambda_{gt} + \gamma_{grt} + u_{grt}.$$

The coefficient β_g^+ measures pass-through associated with productivity gains, while β_g^- measures pass-through associated with productivity losses. Because a_{grt}^- is non-positive, a positive β_g^- implies that productivity losses are associated with wage declines. I also test whether the two pass-through coefficients are equal.

Table 8 reports the pass-through coefficients for positive and negative productivity changes for the 1980–1999 and 2000–2019 periods. In the 1980–1999 period, the pass-through coefficient on gains exceeds the pass-through coefficient on losses for five of the six worker types, but none of the differences is statistically significant. In the 2000–2019 period, the pass-through coefficients on both productivity gains and productivity losses are close to zero across all six worker types, and the estimated differences between them are also close to zero. This pattern suggests that weak pass-through in the later period is not confined to one direction of productivity change.

Table 8: Pass-through of positive and negative productivity changes

	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
	1980–1999			1980–1999		
Positive	0.206 (0.094)	0.303 (0.064)	0.368 (0.147)	0.029 (0.081)	0.131 (0.073)	0.406 (0.094)
Negative	0.146 (0.324)	0.189 (0.144)	0.356 (0.212)	0.578 (0.322)	0.036 (0.451)	0.348 (0.331)
Difference	0.060 (0.396) {0.873}	0.114 (0.189) {0.529}	0.012 (0.308) {0.966}	–0.549 (0.385) {0.276}	0.095 (0.444) {0.813}	0.057 (0.379) {0.892}
	2000–2019			2000–2019		
Positive	0.028 (0.031)	0.038 (0.030)	–0.026 (0.086)	0.035 (0.046)	0.016 (0.024)	–0.058 (0.064)
Negative	0.018 (0.022)	0.046 (0.014)	–0.018 (0.055)	0.047 (0.032)	0.020 (0.023)	–0.057 (0.051)
Difference	0.010 (0.024) {0.561}	–0.008 (0.034) {0.730}	–0.008 (0.128) {0.986}	–0.013 (0.044) {0.752}	–0.004 (0.031) {0.874}	–0.002 (0.112) {0.963}

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of Bell and McCaffrey (2002). Region and year fixed effects and region-specific trends are included. “Difference” is the pass-through coefficient on positive productivity changes minus the pass-through coefficient on negative productivity changes. The p -values in curly brackets are based on wild bootstrap tests of equality between the two pass-through coefficients, with 5,000 replications and clustering at the region level.

8.3 Contemporaneous and lagged changes

The decline in productivity pass-through could partly reflect slower wage adjustment to productivity. If wage adjustment takes longer in the later period, part of the adjustment may occur with a one-year lag. The pass-through coefficient on the contemporaneous productivity environment may then appear smaller when only that productivity environment is included. I examine this possibility by allowing wages to depend on the contemporaneous productivity environment and its one-year lag. For this analysis, I construct annual productivity environments using equation (1), after linearly interpolating employment for each worker type, establishment type, and region, as well as male and female hours for each establishment type and region in the 1981–1984 and 1986–1988 periods. Wages are not interpolated. For each worker type, I estimate the pass-through of contemporaneous and lagged productivity environments jointly:

$$w_{grt} = \beta_g^0 a_{grt} + \beta_g^{-1} a_{gr,t-1} + \mu_{gr} + \lambda_{gt} + \gamma_{gr} t + u_{grt}.$$

The coefficient β_g^0 measures the pass-through of the contemporaneous productivity environment conditional on the lagged productivity environment, while β_g^{-1} measures the pass-through of the lagged productivity environment conditional on the contemporaneous productivity environment. I also report $\beta_g^0 + \beta_g^{-1}$, which measures the pass-through of a productivity increase that is present in both the current and preceding years. I then test whether the sum of the two pass-through coefficients is equal to zero.

Table 9 reports the pass-through coefficients on the contemporaneous and lagged productivity environments and their sum for the 1980–1999 and 2000–2019 periods. The sum is smaller in the 2000–2019 period than in the 1980–1999 period for all six worker types. In the 1980–1999 period, the sum is positive for all six worker types and statistically different from zero at the 10 percent level. The pass-through coefficient on the lagged productivity environment is larger for prime-age and older men than for the other worker types. Consequently, the sum of the two pass-through coefficients exceeds the pass-through coefficient on the contemporaneous productivity environment for these groups. For younger men and women in all three age groups, the pass-through coefficients on the lagged productivity environment are smaller, and the pass-through coefficients on the contemporaneous productivity environment account for most of the sum. In the 2000–2019 period, the pass-through coefficient on the lagged productivity environment is positive for prime-age men and for younger and prime-age women. The results provide little evidence that the decline reflects a shift from contemporaneous wage adjustment to adjustment with a one-year lag.

8.4 Production and non-production workers

The decline in productivity pass-through could partly reflect changes in the composition of employment between production and non-production occupations if productivity pass-through

Table 9: Pass-through of contemporaneous and lagged productivity changes

	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
	1980–1999			1980–1999		
Contemporaneous	0.078 (0.062)	0.137 (0.046)	0.235 (0.177)	0.144 (0.060)	0.153 (0.100)	0.325 (0.116)
Lagged	0.040 (0.050)	0.109 (0.037)	0.151 (0.148)	–0.009 (0.041)	0.031 (0.080)	0.019 (0.109)
Total	0.118 (0.064) {0.096}	0.246 (0.058) {0.027}	0.386 (0.081) {0.035}	0.135 (0.056) {0.100}	0.184 (0.094) {0.071}	0.344 (0.086) {0.004}
	2000–2019			2000–2019		
	16–29	30–54	55–74	16–29	30–54	55–74
	1980–1999			1980–1999		
Contemporaneous	0.024 (0.024)	0.042 (0.017)	–0.024 (0.035)	0.043 (0.032)	0.020 (0.016)	–0.058 (0.016)
Lagged	–0.005 (0.020)	0.013 (0.019)	–0.041 (0.024)	0.023 (0.058)	0.031 (0.028)	–0.019 (0.036)
Total	0.019 (0.041) {0.657}	0.055 (0.032) {0.101}	–0.064 (0.039) {0.226}	0.066 (0.075) {0.347}	0.051 (0.040) {0.243}	–0.077 (0.042) {0.161}

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of [Bell and McCaffrey \(2002\)](#). Region and year fixed effects and region-specific trends are included. “Total” is the sum of the pass-through coefficients on the contemporaneous and lagged productivity environments. The *p*-values in curly brackets are based on wild bootstrap tests of the null hypothesis that the sum equals zero, with 5,000 replications and clustering at the region level.

differs between the two groups. The framework in Section 5 also provides a way to interpret such differences. Production and non-production workers may differ in how productivity affects the firm’s incremental value from retaining the worker because differences in their tasks may make the firm more or less dependent on retaining a particular worker. They may also differ in how productivity affects the worker’s post-separation value because the transferability of skills and employment opportunities available after separation can differ across occupations.

For each worker type, I estimate equation (2) separately for production and non-production workers, with non-production work comprising managerial, clerical, and technical occupations. Because the two groups have different employment shares across industries and establishment sizes, I re-construct the productivity environment separately for each group using equation (1), with the lagged employment shares of workers in that group across establishment types.

Table 10 reports productivity pass-through separately for production and non-production workers for the 1980–1999 and 2000–2019 periods. Productivity pass-through is positive across all six worker types in both occupational groups in the 1980–1999 period and small in magnitude across all six worker types in both groups in the 2000–2019 period. Productivity pass-through is smaller in the 2000–2019 period than in the 1980–1999 period for all six worker types among production workers and for all six worker types among non-production workers. In the 1980–1999 period, the pass-through coefficients for production and non-production workers differ significantly only for younger men. For this group, the coefficient is larger for production workers. For prime-age and older men and for younger and prime-age women,

Table 10: Productivity pass-through by occupation

	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
	1980–1999			1980–1999		
Production	0.222 (0.058)	0.278 (0.041)	0.356 (0.090)	0.137 (0.065)	0.145 (0.071)	0.304 (0.094)
Non-production	0.039 (0.046)	0.238 (0.039)	0.372 (0.142)	0.104 (0.041)	0.131 (0.094)	0.510 (0.235)
Difference	−0.183 (0.067) {0.002}	−0.040 (0.030) {0.211}	0.015 (0.152) {0.909}	−0.033 (0.049) {0.507}	−0.014 (0.116) {0.952}	0.207 (0.312) {0.528}
	2000–2019			2000–2019		
Production	0.010 (0.025)	0.041 (0.029)	−0.001 (0.038)	0.019 (0.034)	0.034 (0.028)	−0.038 (0.013)
Non-production	0.031 (0.018)	0.018 (0.013)	−0.057 (0.049)	−0.003 (0.026)	−0.003 (0.018)	−0.103 (0.060)
Difference	0.021 (0.013) {0.204}	−0.023 (0.021) {0.281}	−0.057 (0.076) {0.462}	−0.023 (0.024) {0.300}	−0.037 (0.034) {0.224}	−0.065 (0.061) {0.457}

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of [Bell and McCaffrey \(2002\)](#). Region and year fixed effects and region-specific trends are included. “Difference” is the pass-through coefficient for non-production workers minus the pass-through coefficient for production workers. The p -values in curly brackets are based on wild bootstrap tests of equality between the two pass-through coefficients, with 5,000 replications and clustering at the region level.

the coefficients for the two occupational groups are similar. For older women, the coefficient is larger for non-production workers, but the difference is not statistically significant. In the 2000–2019 period, none of the differences between production and non-production workers is statistically significant. Changes in the composition of employment between the two occupational groups therefore do not by themselves account for the decline documented in Section 4.

8.5 Permanent and transitory changes

I finally examine whether productivity pass-through differs between the permanent and transitory components of the productivity environment. This distinction is relevant to the framework in Section 5 because permanent and transitory productivity changes may affect the firm’s incremental value from retaining the worker and the worker’s post-separation value differently. I then examine whether the decline in productivity pass-through documented in Section 4 is concentrated in the permanent component or is also present in the transitory component.

Following [Beveridge and Nelson \(1981\)](#), [Harvey \(1989\)](#), and [Morley et al. \(2003\)](#), I decompose log productivity for each establishment type j and region r into a permanent component ζ_{jrt} and a stationary transitory component ξ_{jrt} :

$$a_{jrt} = \zeta_{jrt} + \xi_{jrt}.$$

The permanent component evolves according to

$$\zeta_{jrt} = \zeta_{jr,t-1} + \alpha_t + v_{jrt}^{\zeta},$$

where α_t captures the component of productivity growth common across establishment types and regions in year t , and v_{jrt}^{ζ} is the permanent innovation. The transitory component follows a stationary AR(Q) process,

$$\xi_{jrt} = \sum_{q=1}^Q \phi_q \xi_{jr,t-q} + v_{jrt}^{\xi},$$

where v_{jrt}^{ξ} is the transitory innovation. These equations imply

$$\Delta a_{jrt} = \alpha_t + v_{jrt}^{\zeta} + \Delta \xi_{jrt}.$$

I implement the decomposition by first regressing annual productivity growth on year effects using productivity for all regions and establishment types. For this decomposition, labor input for the 1981–1984 and 1986–1988 periods is constructed using linearly interpolated male and female hours within each establishment type and region. The variances of the permanent and transitory innovations are allowed to vary across establishment types, while the ratio of the variance of the permanent innovation to that of the transitory innovation is common across establishment types and regions. The autoregressive coefficients for the transitory component are also common across establishment types and regions. I then estimate the autoregressive coefficients and innovation variances by Gaussian maximum likelihood for $Q = 1, 2, 3$ and select the specification with the lowest Bayesian information criterion among successfully estimated specifications that satisfy the numerical diagnostics.⁷ This procedure selects $Q = 3$. The variance of the permanent innovation accounts for 48.4 percent of the variance of annual productivity growth, while that of the change in the transitory component accounts for the remaining 51.6 percent. Using the selected specification, I recover the permanent innovations and the transitory component using the Gaussian smoother. I construct the permanent component recursively using the fitted values from the regression on year effects and the recovered permanent innovations. I then construct the permanent and transitory components for workers of each type in each region by aggregating changes in the corresponding components of productivity for establishments of each type using the same procedure as in equation (1). The permanent and transitory components for workers of type g in region r and year t , ζ_{grt} and ξ_{grt} , satisfy $a_{grt} = \zeta_{grt} + \xi_{grt}$.

For each worker type, I estimate the pass-through of the permanent and transitory compo-

⁷The diagnostics exclude a specification if the largest absolute partial autocorrelation is at least 0.990, the largest companion-root modulus is at least 0.995, or the variance of the permanent innovation is at most 10^{-6} times the variance of the transitory innovation.

nents jointly:

$$w_{grt} = \beta_g^\zeta \zeta_{grt} + \beta_g^\xi \xi_{grt} + \mu_{gr} + \lambda_{gt} + \gamma_{grt} + u_{grt}.$$

The coefficient β_g^ζ measures the pass-through of the permanent component of the productivity environment conditional on the transitory component, while β_g^ξ measures the pass-through of the transitory component of the productivity environment conditional on the permanent component.

Table 11 reports the pass-through coefficients on the permanent and transitory components of the productivity environment for the 1980–1999 and 2000–2019 periods. In the 1980–1999 period, the pass-through coefficient on the permanent component is positive and exceeds the pass-through coefficient on the transitory component for five of the six worker types, while the pass-through coefficients on the transitory component are generally less precisely estimated. Between the 1980–1999 period and the 2000–2019 period, the pass-through of the permanent component declines for all six worker types, with the changes statistically significant at the 10 percent level for all three male age groups and for older women. The pass-through of the transitory component does not decline consistently across worker types, and none of the changes in transitory pass-through is statistically significant.

Table 11: Pass-through of permanent and transitory productivity changes

	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
	1980–1999			1980–1999		
Permanent	0.196 (0.074)	0.293 (0.040)	0.357 (0.121)	0.184 (0.084)	0.129 (0.113)	0.409 (0.085)
Transitory	0.150 (0.261)	0.063 (0.110)	0.472 (0.365)	−0.103 (0.199)	−0.057 (0.179)	0.178 (0.219)
	2000–2019			2000–2019		
Permanent	0.041 (0.032)	0.080 (0.032)	−0.089 (0.066)	0.088 (0.067)	0.074 (0.071)	−0.097 (0.042)
Transitory	−0.002 (0.067)	−0.010 (0.022)	0.065 (0.017)	−0.017 (0.079)	−0.050 (0.089)	−0.009 (0.046)
	Change			Change		
Permanent	−0.155 (0.080) {0.086}	−0.213 (0.058) {0.025}	−0.445 (0.161) {0.049}	−0.096 (0.111) {0.406}	−0.055 (0.170) {0.736}	−0.506 (0.077) {0.004}
Transitory	−0.152 (0.265) {0.627}	−0.073 (0.110) {0.584}	−0.408 (0.361) {0.289}	0.085 (0.186) {0.663}	0.007 (0.201) {0.991}	−0.187 (0.212) {0.346}

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of Bell and McCaffrey (2002). Region and year fixed effects and region-specific trends are included. “Change” is the 2000–2019 estimate minus the 1980–1999 estimate. The p -values in curly brackets are based on wild bootstrap tests of no change in the corresponding coefficients, with 5,000 replications and clustering at the region level.

9 Conclusion

This paper documents a substantial decline in productivity pass-through to wages in Japanese manufacturing over four decades. Productivity pass-through is positive and often sizable in earlier periods, but generally declines over time and becomes small across all six worker types in later periods. This decline is concentrated primarily in pass-through into unweighted mean wage growth rather than in pass-through into changes in the relative wage structure across job types or employment reallocation across job types.

Productivity pass-through is generally larger for productivity changes with broader regional scope. For all six worker types, both the pass-through of the regional component and the pass-through of the prefectural component are smaller in the 2000–2019 period than in the 1980–1999 period. In the 1980–1999 period, the pass-through of the permanent component is generally larger than that of the transitory component, and the pass-through of the permanent component declines between the two periods for all six worker types.

The bargaining framework provides a way to interpret these patterns. Productivity pass-through depends on how productivity gains affect the firm’s incremental value from retaining the worker and the worker’s post-separation value. A change in productivity pass-through can therefore arise from changes in either of the two productivity elasticities or their relative weight and does not necessarily imply a change in the worker’s bargaining weight. Empirically, for all six worker types, the estimates of productivity pass-through into unweighted mean wage growth are lower in production environments with higher capital intensity and in labor-market environments with higher employment concentration and a greater prevalence of part-time employment. I then quantify the changes in pass-through implied by the observed changes in these characteristics from 1980 to 2019. The implied reduction from the increase in capital intensity is the largest for all six worker types.

Counterfactual accounting shows that the decline in productivity pass-through contributes more to the difference between counterfactual and actual wages in 2019 than the slowdown in productivity growth for all six worker types. Understanding long-run wage stagnation therefore requires considering not only the rate of productivity growth but also the extent to which productivity growth passes through into wages.

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Appendix

A Wages and Employment across Job Types

Figure A1 reports real hourly wages across job types within each worker type in 1980, 2000, and 2019. Both the levels and changes in wages differ substantially across job types within each worker type. Wages generally increase between 1980 and 2000. Among prime-age and older men, wage growth becomes much weaker between 2000 and 2019, and wages decline in several job types. Wage levels for prime-age and older men are relatively high in job types involving non-production work in medium and large establishments, particularly in material- and capital-goods manufacturing. Wage differences across job types are less pronounced among younger men. Among prime-age and older women, wages generally continue to increase between 2000 and 2019. The size of the increase differs considerably across job types.

Figure A2 reports employment shares across job types within each worker type in 1980, 2000, and 2019. The shares sum to one across job types within each worker type and year. Both the levels and changes in employment shares differ substantially across job types within each worker type. Employment shares across job types differ substantially across worker types. Among prime-age men, employment shares increase in several job types in capital-goods manufacturing, particularly in medium and large establishments. Among prime-age women, employment shares decline in several job types involving production work in medium and large establishments, while changes in job types involving non-production work are more mixed. Among younger and older workers, changes in employment shares also differ across job types.

B Derivations

B.1 Derivation for the wage decomposition

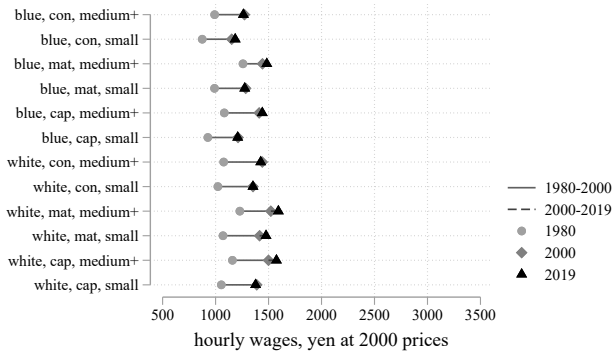
Average log wages satisfy

$$w_{grt} = \underbrace{\bar{w}_{grt}}_{\text{cell-wage}} + \sum_h \tilde{s}_{ghrt} \tilde{w}_{ghrt}. \quad (\text{A1})$$

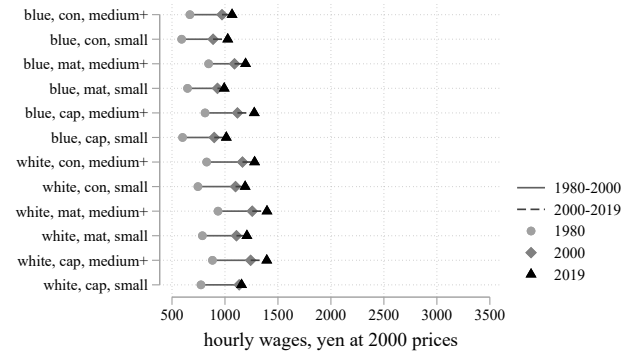
Equation (A1) applies the accounting identity in Olley and Pakes (1996) to the average log wages within each worker type. Employment shares sum to one, and deviations from the unweighted averages across job types sum to zero. When employment shares are used as weights, the average log wages for each worker type can be written as the unweighted average across job types of the average log wages within each job type plus the second term in equation (A1). The decomposition below is closely related to the one developed in Yamada (2026), who combines a shift-share decomposition with an augmented Olley–Pakes decomposition to study changes in average log real hourly wages across a broad set of industries in Japan. The decomposition is formulated in levels here and in changes in Yamada (2026).

Figure A1: Hourly wages by worker type and job type

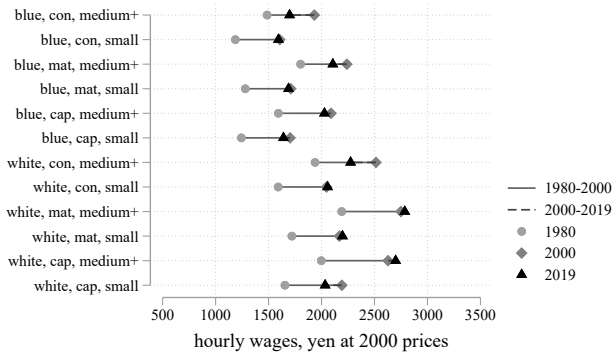
(a) Men, 16–29



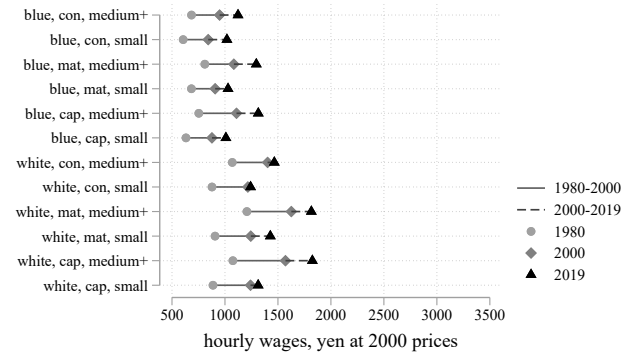
(b) Women, 16–29



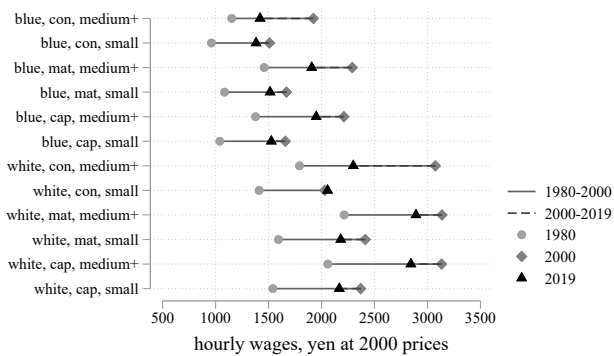
(c) Men, 30–54



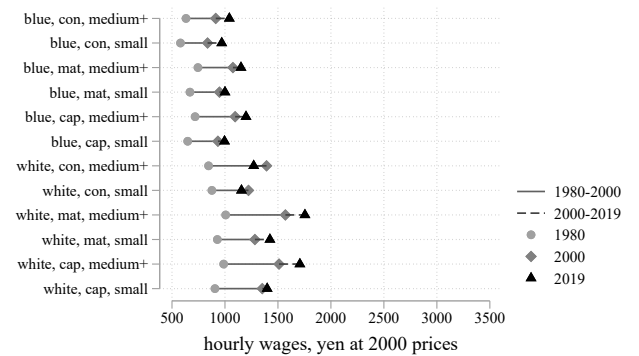
(d) Women, 30–54



(e) Men, 55–74



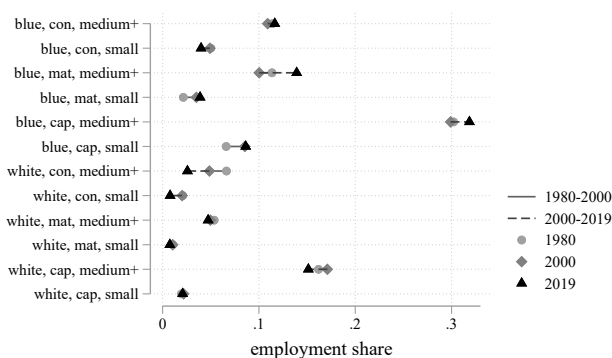
(f) Women, 55–74



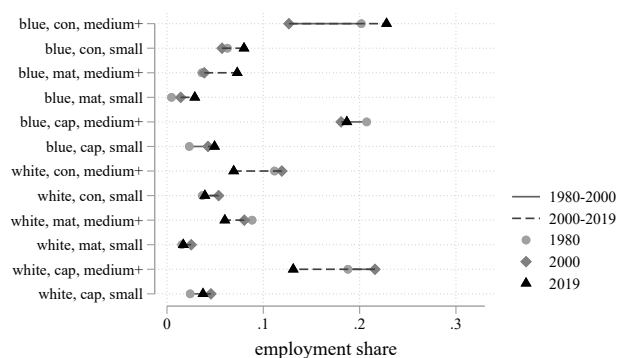
Notes: Wages are measured in yen and deflated to 2000 prices. The line segments connect 1980 to 2000 and 2000 to 2019, respectively. The labels “blue” and “white” denote production work and managerial, clerical, and technical work, “con”, “mat”, and “cap” denote consumption-goods, material-goods, and capital-goods manufacturing, and “medium+” and “small” denote establishments with 30 or more regularly employed workers and establishments with fewer than 30.

Figure A2: Employment shares by worker type and job type

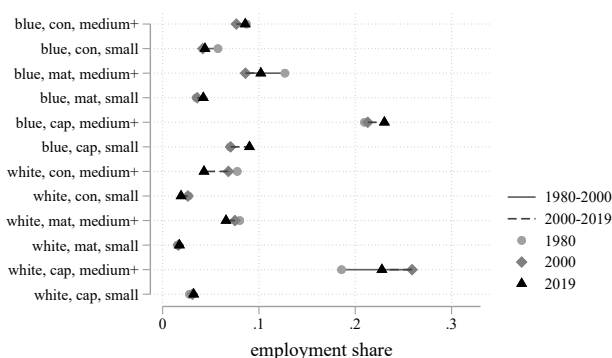
(a) Men, 16–29



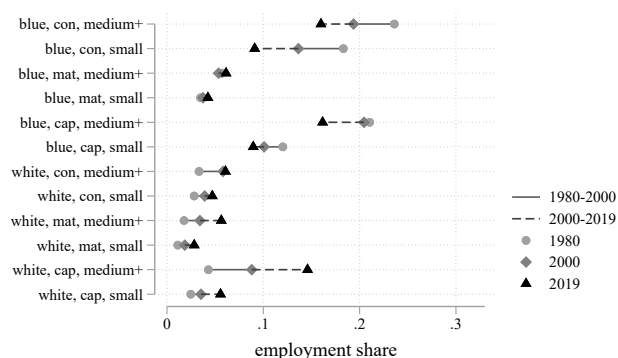
(b) Women, 16–29



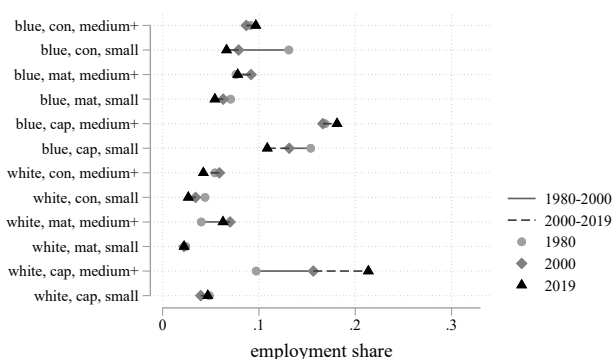
(c) Men, 30–54



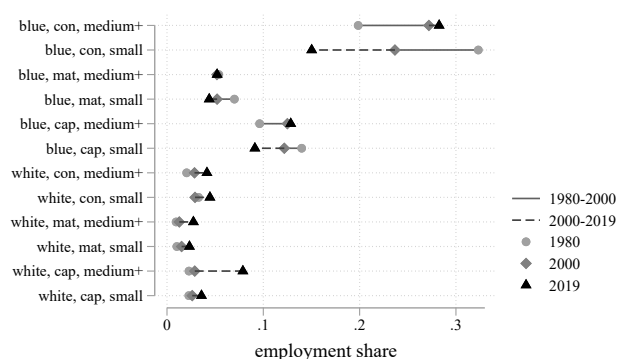
(d) Women, 30–54



(e) Men, 55–74



(f) Women, 55–74



Notes: Employment shares are measured within each worker type and sum to one across job types in each worker type and year. The line segments connect 1980 to 2000 and 2000 to 2019, respectively. The labels “blue” and “white” denote production work and managerial, clerical, and technical work, “con”, “mat”, and “cap” denote consumption-goods, material-goods, and capital-goods manufacturing, and “medium+” and “small” denote establishments with 30 or more regularly employed workers and establishments with fewer than 30.

Using the notation defined in Section 3.5, the second term in equation (A1) can then be written exactly as

$$\begin{aligned} \tilde{s}_{ghrt} \tilde{w}_{ghrt} = & \underbrace{\frac{1}{2} (\tilde{s}_{ghrt} + \bar{\tilde{s}}_{ghr}) (\tilde{w}_{ghrt} - \bar{\tilde{w}}_{ghr})}_{\text{relative-wage}} \\ & + \underbrace{\frac{1}{2} (\tilde{w}_{ghrt} + \bar{\tilde{w}}_{ghr}) (\tilde{s}_{ghrt} - \bar{\tilde{s}}_{ghr})}_{\text{relative-share}} + \underbrace{\bar{\tilde{w}}_{ghr} \bar{\tilde{s}}_{ghr}}_{\text{time-invariant}}. \quad (\text{A2}) \end{aligned}$$

The relative-wage component evaluates deviations of relative log wages from their time averages over the relevant estimation period at the midpoints between current relative employment shares and their time averages over the same period. The relative-share component evaluates deviations of relative employment shares from their time averages over the relevant estimation period at the midpoints between current relative log wages and their time averages over the same period. The interaction between the deviations in relative log wages and relative employment shares is therefore divided equally between the two components.

Summing equation (A2) across job types and substituting it into equation (A1) yields equation (3) in the main text. The final term in equation (A2) depends only on time averages over the relevant estimation period and is therefore constant over time within each worker type, job type, and region. Its sum across job types is constant over time within each worker type and region and is absorbed by the region fixed effects in equation (2).

B.2 Derivation for the counterfactual decomposition

From the definitions in Section 4.3, the difference between counterfactual and actual average log wages can be written as

$$w_{grt}^{cf} - w_{grt} = \beta_g^1 \Delta a_{grt}^1 - \beta_g^2 \Delta a_{grt}^2.$$

When the pass-through estimate for the 1980–1999 period is used as the reference, this equation can be decomposed as

$$w_{grt}^{cf} - w_{grt} = \beta_g^1 (\Delta a_{grt}^1 - \Delta a_{grt}^2) + \Delta a_{grt}^2 (\beta_g^1 - \beta_g^2).$$

When the pass-through estimate for the 2000–2019 period is used as the reference, it can be decomposed as

$$w_{grt}^{cf} - w_{grt} = \beta_g^2 (\Delta a_{grt}^1 - \Delta a_{grt}^2) + \Delta a_{grt}^1 (\beta_g^1 - \beta_g^2).$$

Averaging the two equations above gives equation (4).

C Additional Results

C.1 Bonus

Productivity changes may be related to changes in bonuses as well as wages. This section examines whether the decline in productivity pass-through into hourly wages is offset by stronger pass-through into the bonus ratio. Let W_{ghrt} denote the real hourly wages excluding bonuses for workers of type g in jobs of type h , region r , and year t and B_{ghrt} denote the real hourly bonuses. The logarithm of the real hourly wages including bonuses can then be written as

$$\ln(W_{ghrt} + B_{ghrt}) = \ln W_{ghrt} + \ln \left(1 + \frac{B_{ghrt}}{W_{ghrt}} \right).$$

I refer to the second term as the bonus ratio and aggregate it across job types using the employment shares defined in Section 3.5. Because bonuses reported in survey year t refer to payments received in the preceding year, bonuses are assigned to year $t - 1$. Consequently, the estimation period ranges from 1989 to 2018. I re-estimate equation (2) separately for hourly wages and the bonus ratio. Hourly wages are constructed in the same way as those used in Table 1, but the estimation periods differ.

Table A1: Productivity pass-through into hourly wages and the bonus ratio

	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
	1989–2008			1989–2008		
Hourly wages	0.096 (0.064)	0.147 (0.058)	0.242 (0.130)	0.211 (0.071)	0.147 (0.101)	0.205 (0.163)
Bonus ratio	0.041 (0.016)	0.048 (0.024)	0.048 (0.033)	0.005 (0.022)	0.035 (0.024)	0.061 (0.034)
	1999–2018			1999–2018		
Hourly wages	0.018 (0.026)	0.035 (0.014)	−0.018 (0.035)	0.036 (0.033)	0.007 (0.019)	−0.059 (0.014)
Bonus ratio	0.003 (0.006)	−0.011 (0.013)	−0.002 (0.021)	0.015 (0.015)	−0.005 (0.010)	−0.008 (0.006)
	Change			Change		
Hourly wages	−0.078 (0.046)	−0.112 (0.049)	−0.260 (0.115)	−0.175 (0.079)	−0.141 (0.097)	−0.264 (0.160)
	{0.122}	{0.092}	{0.061}	{0.119}	{0.295}	{0.152}
Bonus ratio	−0.038 (0.016)	−0.059 (0.027)	−0.050 (0.037)	0.010 (0.031)	−0.040 (0.022)	−0.069 (0.032)
	{0.013}	{0.093}	{0.234}	{0.770}	{0.175}	{0.108}

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of Bell and McCaffrey (2002). Region and year fixed effects and region-specific trends are included. “Change” is the 1999–2018 estimate minus the 1989–2008 estimate. The p -values in curly brackets are based on wild bootstrap tests of no change in the corresponding coefficients, with 5,000 replications and clustering at the region level.

Table A1 reports estimates of the relationship of the productivity environment with hourly wages and the bonus ratio for the 1989–2008 period and the 1999–2018 period. In the 1999–2018

period, the relationship between the bonus ratio and the productivity environment is weak across all six worker types, and the pass-through coefficients for hourly wages are also substantially smaller. Thus, the decline in productivity pass-through into hourly wages is not offset by a stronger relationship between the bonus ratio and the productivity environment.

C.2 Employment

Productivity changes may be related to changes in employment as well as wages. This section examines whether the decline in productivity pass-through to wages is accompanied by a change in the relationship between employment and the productivity environment. The dependent variable is log employment for workers of type g in region r and year t . Employment is calculated from the employment sample as the sum of the weights defined in Section 3.1 for each worker type, region, and year. The specification otherwise follows equation (2), including region-specific trends.

Table A2: Employment and productivity

	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
1980–1999	0.528 (0.206)	0.175 (0.087)	0.207 (0.268)	0.158 (0.270)	–0.064 (0.078)	–0.401 (0.212)
2000–2019	0.039 (0.086)	0.115 (0.054)	0.172 (0.096)	–0.039 (0.127)	0.253 (0.137)	0.275 (0.159)
Change	–0.489 (0.205) {0.064}	–0.060 (0.093) {0.478}	–0.034 (0.257) {0.900}	–0.197 (0.227) {0.376}	0.317 (0.117) {0.028}	0.676 (0.146) {0.002}

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of [Bell and McCaffrey \(2002\)](#). Region and year fixed effects and region-specific trends are included. The dependent variable is log employment for each worker type. “Change” is the 2000–2019 estimate minus the 1980–1999 estimate. The p -values in curly brackets are based on wild bootstrap tests of no change in the corresponding coefficients, with 5,000 replications and clustering at the region level.

Table A2 reports estimates of the relationship between employment and the productivity environment in the 1980–1999 period and the 2000–2019 period. The relationship between employment and the productivity environment differs considerably across worker types. In the 1980–1999 period, the coefficient estimates are positive for all three male age groups and for younger women, but negative for prime-age and older women. In the 2000–2019 period, the estimates remain positive for all three male age groups, become positive for prime-age and older women, and are slightly negative for younger women. The estimates decline between the two periods for all three male age groups and for younger women, whereas they increase for prime-age and older women. The decline is statistically significant at the 10 percent level for younger men, while the increases are statistically significant at the 5 percent level for prime-age and older women. Unlike productivity pass-through to wages, the relationship between employment and the productivity environment does not decline across all six worker types.

C.3 Adjusting for worker attributes

The unweighted mean of wage growth by job type may partly reflect changes in worker attributes within each worker type and job type. I adjust for changes in worker attributes that are consistently available throughout the sample period using the re-weighting approach of [DiNardo et al. \(1996\)](#). I re-weight each worker using the inverse of the predicted probability of belonging to that year from a logit model that includes age, age squared, job tenure, job tenure squared, part-time status, and region. I then re-construct the cell-wage component so that the distribution of worker attributes is held fixed across years in each estimation period within each worker type and job type.

Table A3 reports the estimates of productivity pass-through into the cell-wage component when equation (2) is re-estimated using the adjusted cell-wage component. Productivity pass-through declines between the 1980–1999 period and the 2000–2019 period for all six worker types. The estimates are generally similar to those for the cell-wage component in Table 2. The decline in pass-through into the cell-wage component remains after adjusting for changes in worker attributes.

Table A3: Productivity pass-through into the cell-wage component adjusted for worker attributes

(a) Men						
	16–29		30–54		55–74	
1980–1999	0.130 (0.040)	0.175 (0.037)	0.235 (0.059)	0.291 (0.045)	0.401 (0.124)	0.377 (0.083)
2000–2019	0.007 (0.022)	0.009 (0.022)	0.019 (0.019)	0.025 (0.020)	–0.039 (0.032)	–0.047 (0.031)
Change	–0.122 (0.040) {0.004}	–0.166 (0.037) {0.002}	–0.215 (0.060) {0.011}	–0.266 (0.049) {0.027}	–0.440 (0.107) {0.002}	–0.424 (0.084) {0.004}
Trends	No	Yes	No	Yes	No	Yes
(b) Women						
	16–29		30–54		55–74	
1980–1999	0.152 (0.049)	0.185 (0.035)	0.198 (0.020)	0.197 (0.049)	0.200 (0.085)	0.400 (0.103)
2000–2019	–0.007 (0.033)	–0.011 (0.035)	–0.008 (0.019)	0.008 (0.018)	–0.022 (0.027)	–0.040 (0.014)
Change	–0.159 (0.065) {0.028}	–0.196 (0.054) {0.035}	–0.206 (0.029) {0.000}	–0.189 (0.041) {0.006}	–0.222 (0.093) {0.063}	–0.440 (0.103) {0.005}
Trends	No	Yes	No	Yes	No	Yes

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of [Bell and McCaffrey \(2002\)](#). Region and year fixed effects are included in all columns. Region-specific trends are included in even-numbered columns. “Change” is the 2000–2019 estimate minus the 1980–1999 estimate. The p -values in curly brackets are based on wild bootstrap tests of no change in pass-through coefficients, with 5,000 replications and clustering at the region level.

C.4 Predetermined production and labor-market environments

Section 6 shows that productivity pass-through into the cell-wage component varies with capital intensity, employment concentration, and the prevalence of part-time employment. This section examines whether the results are similar when these characteristics are measured using lagged values. I re-estimate equation (6) using predetermined production and labor-market characteristics. For 1985 and 1989, the lagged values are those in 1980 and 1985, respectively; from 1990 onward, they are those in the preceding year.

Table A4: Productivity pass-through into the cell-wage component across predetermined production and labor-market environments

(a) Capital intensity						
	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
a_{grt}^c	0.030 (0.020)	0.057 (0.020)	0.032 (0.028)	0.024 (0.032)	0.019 (0.012)	0.043 (0.017)
z_{grt}^c	–0.016 (0.014)	0.013 (0.010)	0.006 (0.015)	–0.001 (0.012)	0.020 (0.010)	0.035 (0.025)
$a_{grt}^c \times z_{grt}^c$	–0.061 (0.008)	–0.076 (0.022)	–0.131 (0.045)	–0.038 (0.021)	–0.065 (0.010)	–0.102 (0.053)
(b) Employment concentration						
	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
a_{grt}^c	0.031 (0.018)	0.061 (0.020)	0.025 (0.022)	0.017 (0.026)	0.029 (0.016)	0.057 (0.026)
z_{grt}^c	–1.757 (1.480)	–0.568 (2.594)	5.458 (3.615)	–5.900 (4.377)	–5.772 (4.736)	–4.858 (12.467)
$a_{grt}^c \times z_{grt}^c$	–6.563 (1.968)	–6.050 (2.663)	–1.884 (3.892)	–11.148 (5.926)	–11.487 (8.966)	–11.631 (14.991)
(c) Part-time employment						
	Men			Women		
	16–29	30–54	55–74	16–29	30–54	55–74
a_{grt}^c	0.030 (0.022)	0.061 (0.025)	0.023 (0.025)	0.028 (0.032)	0.036 (0.027)	0.069 (0.040)
z_{grt}^c	–0.144 (0.066)	0.088 (0.112)	0.085 (0.178)	–0.105 (0.066)	0.051 (0.095)	–0.045 (0.080)
$a_{grt}^c \times z_{grt}^c$	–0.215 (0.156)	–0.336 (0.219)	–0.146 (0.307)	–0.405 (0.165)	–0.584 (0.156)	–0.521 (0.324)

Notes: Standard errors in parentheses are clustered at the region level and corrected using the degrees-of-freedom adjustment of Bell and McCaffrey (2002). Region and year fixed effects and region-specific trends are included. The variables a_{grt} and z_{grt} are centered at their respective means for the corresponding worker type, and z_{grt} is log capital intensity in panel (a), employment concentration in panel (b), and the part-time employment share in panel (c).

Table A4 reports the estimates of the coefficients in equation (6) when production and labor-market characteristics are measured using lagged values. The estimates of productivity

pass-through into the cell-wage component are lower with higher capital intensity, employment concentration, and part-time employment for all six worker types, as in Table 4. The estimates are similar to those using contemporaneous characteristics.