Bank of Japan Working Paper Series

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Yosuke Kido [*]
ykido@imf.org

Kotaro Suita [**]
koutarou.suita@boj.or.jp

No.25-E-5
April 2025

Bank of Japan
2-1-1 Nihonbashi-Hongokucho, Chuo-ku, Tokyo 103-0021, Japan

[*] International Monetary Fund
[**] Research and Statistics Department, Bank of Japan (currently at the Personnel and Corporate Affairs Department)

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Labor Cost Passthrough:
Evidence from Japanese Long-term Subnational Data*

Yosuke Kido[†] Kotaro Suita[‡]

April 2025

Abstract

In this paper, we analyze labor cost passthrough to price inflation in the pre-pandemic period in Japan, utilizing novel long-term subnational datasets. In the first part of the paper, we construct a long-term prefecture-level dataset of productivity-adjusted labor costs, service prices and local labor market tightness, utilizing relevant disaggregate prefectural data and applying prefecture-level Panel Vector Autoregression to study the interlinkages of the variables. We find statistically significant labor cost passthrough to service prices at the local level for the sample of fiscal year 1985-2018, but also find that the passthrough weakened for the sample after the mid-1990s, when Japan entered low inflation phase. In addition, by utilizing the R-JIP database, the industry-prefectural data available from the 1970s, we find that both the services and manufacturing sectors experienced a decline in labor cost passthrough to the value-added deflators after the mid-1990s. We also find statistically significant asymmetric labor cost passthrough characterized by larger upward passthrough compared to downward passthrough (often called the *rockets and feathers effect*) in the services sector for the period before the mid-1990s, but such asymmetric effects disappeared in the post-mid 1990s period.

JEL Classification: E31, J31, R10
Keywords: Wages, Prices, Inflation, Passthrough, Subnational data

* The authors would like to thank Kosuke Aoki, Ichiro Fukunaga, Naoya Kato and Yusuke Takahashi for helpful comments and suggestions. Any remaining errors are attributable to the authors. The paper does not necessarily reflect views of Bank of Japan, International Monetary Fund, its management, or Executive Board.

† International Monetary Fund (ykido@imf.org)

‡ Research and Statistics Department, Bank of Japan (currently at the Personnel and Corporate Affairs Department) (koutarou.suita@boj.or.jp)

1. Introduction

Labor costs are highly relevant for price inflation, and their linkages are envisaged in theoretical models. However, empirical findings are rather mixed. Some studies prior to the pandemic suggest a long-term decline in the passthrough of labor costs to price inflation, especially in the U.S. (Heise et al., 2022; Peneva and Rudd, 2017). After the pandemic, this topic attracts renewed attention as some studies point to an increase of wage-to-price passthrough in the post-pandemic period (e.g. Amiti et al., 2024).

This paper aims to provide additional empirical evidence on labor cost passthrough to price inflation using novel subnational datasets for Japan. Japan provides a unique context for investigation due to its varied inflation dynamics over time, including a prolonged low inflation environment in the pre-pandemic period after mid-1990s (e.g., Fukunaga et al., 2024a, 2024b). Importantly, Japan went through multiple business cycles in the low inflation environment, which offers valuable observations in analyzing the changes in price-wage nexus over time. Despite the importance of the topic, the relevant empirical study on Japan remains relatively underexplored and largely limited to the Phillips curve framework (e.g. Muto, 2009).

Our research leverages novel long-term subnational datasets. Specifically, we construct long-term prefecture-level economic indicators based on relevant data and employ Panel Vector Autoregression from the sample of fiscal year 1985 to 2018. Panel Vector Autoregression directly links relevant local labor costs to local prices, allowing for the interlinkages of the macroeconomic variables, while significantly expanding the sample size utilizing prefecture-level information. Japan's 47 prefectures offer rich information that goes beyond the aggregate national level data, as individual prefectural developments may be obscured at the aggregate level. There are number of studies that utilize Japanese prefecture-level data, such as Brückner and Tuladhar (2014) and Kameda et al. (2021), but application on prices and wages remains limited. Furthermore, given that Japan experienced different inflation phases in the sample period, we conduct subsample analysis to analyze potential changes in behaviors of the macroeconomic variables to the shocks, including labor cost passthrough to prices, as well as other interlinkages of macroeconomic variables. In addition to that, in the extended analysis, using the novel industry-prefecture data available from the 1970s called R-JIP dataset compiled by Research Institute of Economy, Trade and Industry (RIETI), we also analyze labor cost passthrough to value added deflators in the services and manufacturing sectors, including directional asymmetry of labor cost passthrough, as well as a change in passthrough after mid-1990s when Japan entered a low inflation phase.

This paper offers some important findings on passthrough of labor costs to price inflation. Based on Japanese prefecture-level data from fiscal year 1985-2018, we find that passthrough of productivity-adjusted labor cost inflation to local service price inflation is about 0.17 over two years, and 0.25 over five years.[1] These results are broadly similar to Heise et al. (2022), which analyze passthrough of wage to producer service prices using the U.S. industry-level data for 2003-2016, and Peneva and Rudd (2017), which analyze time-varying responses of core inflation to Employment Cost Index-based trend labor cost growth in the U.S. using the time-varying parameter vector autoregression model with stochastic volatility. However, our estimated passthrough is lower than those reported by Ampudia et al. (2024), which analyze labor cost passthrough to producer prices based on Euro area industry-level data for 2009-2023. In addition, we observe a decline in passthrough over time during the sample period, especially for the data post-mid-1990s, where Japan faced low inflation, which is similar to the findings of Peneva and Rudd (2017).[2] Furthermore, in addition to labor cost passthrough, we also find evidence that local labor cost inflation became unresponsive to local services prices and local labor market tightness in the post-mid-1990s subsample period, which are consistent with findings in the literature.

Additionally, utilizing the R-JIP industry-prefecture database, this paper also offers additional novel insights. We find that labor share-adjusted labor cost passthrough to value-added deflators declined in both the services and manufacturing sectors after the mid-1990s, with a more pronounced decline in the manufacturing sector in the near-term horizon, similar to the observation in the U.S. by Heise et al. (2022). Additionally, we find asymmetric labor cost passthrough in the services sector prior to the mid-1990s, characterized by larger upward passthrough compared to downward passthrough (often referred as the *rockets and feathers effect*), a phenomenon frequently found in the exchange rate and commodity price passthrough literature. However, these asymmetric effects in the services sector diminished after the mid-1990s.

The novelty of our paper is two-fold. First, we utilize subnational data to analyze the

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[1] In Japan, the fiscal year starts in April and ends in March of the following year. Thus, our analysis covers period just before the pandemic.

[2] It should be noted that this trend in Japan may have reversed in the post-pandemic period, which is not covered in our paper. For example, using a dynamic factor model, Ueno (2024) finds that underlying trends of wage and price inflation recoupled to some extent in the post-pandemic era, after showing a decoupling in the late 1990s.

interlinkage between wages and prices. Subnational data provides rich information and has been increasingly employed in macroeconomic research, including studies by Hazell et al. (2022). In this context, we construct a novel long-term prefecture-level dataset for Japan, based on relevant disaggregate wage and price data, while controlling for local labor productivity to calculate productivity-adjusted labor cost inflation. Utilizing this prefecture-level dataset, we uncover interlinkages among local labor costs, local non-tradable prices, and local labor market tightness, including labor cost passthrough to prices. To our limited knowledge, this paper represents the first attempt to analyze the price-wage nexus at the Japanese subnational level, and such a subnational analysis is also novel in an international context. We further utilize novel industry-prefecture level data for an extended labor cost analysis in the services and manufacturing sectors and find evidence on asymmetric passthrough, with larger upward passthrough.

Second, by utilizing long-term Japanese subnational data, this paper sheds light on changes in the labor cost passthrough to price inflation before the pandemic. Theoretical papers such as Taylor (2000), Ball and Mankiw (1994), Devereux and Yetman (2010) and Kurozumi (2016) predict that price-setting behaviors can be influenced by trend inflation. Japan's data is particularly suitable for examining these theoretical predictions and the associated potential structural changes, given the prolonged low-inflationary period experienced after the mid-1990s. Consistent with the theoretical predictions, we find evidence that labor cost passthrough to price inflation declined in the post-mid-1990s period both with prefectural and industry-prefecture data. More interestingly, we find that the asymmetric labor cost passthrough observed in the services sector before the mid-1990s diminished in the post-mid-1990s period. While some studies point to asymmetric passthrough, there are few studies arguing changes in the patterns of asymmetric passthrough, particularly regarding labor cost passthrough.

Our paper focuses on the pre-pandemic period due to the availability of subnational data. Globally, several studies indicate an increase in labor cost passthrough (e.g. Amiti et al., 2024 for the U.S.; Ampudia et al., 2024 for Euro area). Relatedly, some studies on Japan also highlight changes in inflation dynamics and the labor market in the post-pandemic era (e.g., Ueno 2024, Nakamura et al., 2024, Fukunaga et al., 2024a, 2024b, and Hoshi and Kashyap, 2025). In particular, Ueno (2024) observes a recoupling of trends in wage and price inflation in the post-pandemic period, following their decoupling in late 1990s. While the assessment of potential changes in labor cost passthrough in the post-pandemic period should be conducted alongside the accumulation of subnational data in the future, our subsample analysis based on long-term subnational data provides valuable historical insights into potential changes in labor cost passthrough in the post-pandemic period.

The remainder of the paper is organized as follows. Section 2 describes the compilation methods of prefecture-level data and the PVAR model used in this analysis. Section 3 discusses the benchmark results for interlinkages of the macroeconomic variables, including labor cost passthrough to price inflation, and also offers subsample analysis and robustness checks. Section 4 offers extended analysis on labor cost passthrough using novel industry-prefecture data, discussing changes after mid-1990s and asymmetric labor cost passthrough. Section 5 concludes.

2. Data and empirical framework

In this section, we discuss the prefecture-level database constructed for this paper and explain the empirical methodology used for benchmark panel analysis in Section 3. Appendix I also provides details about the prefecture-level data.

2.1. Prefecture-level data

Analyzing the interlinkage between wages and prices utilizing subnational data offers advantages over aggregate data, as it allows for an examination of the relationship between local labor costs and corresponding local prices. Regional data have been increasingly used in the empirical literature on prices and wages (e.g., Hazell et al., 2022; Hazell and Taska, forthcoming). In the context of Japan, while prefectural data are used in some empirical studies on fiscal policy (e.g., Brückner and Tuladhar, 2014; Kameda et al., 2021), the use of prefectural data on analysis of wages and prices have been limited (Nishizaki and Watanabe, 2000; Kishaba and Okuda, 2023; Ueda, 2024).

In this paper, we construct a new panel dataset of 47 prefectures at an annual frequency, including labor costs, prices, and labor market tightness, based on relevant disaggregate data. For the price data, we construct a prefecture-level price index based on subgroup-level prefectural data. In our empirical strategy, we focus on non-tradable service items (specifically, general services), which correspond to local labor costs, and exclude tradable goods and administrative as they do not necessarily reflect local labor costs. This approach is similar to that of Hazell et al. (2022), which analyze the slope of Phillips curve based on state-level service prices in the United States. Since a general service price index is not published at the prefectural level, we construct a prefecture-level service price index based on relevant subgroup data. Specifically, we calculate the following:

$$P_{i,t} = \sum_{j=1}^{N} W_{i,j} \times P_{i,j,t}, \qquad (1)$$

where $P_{i,t}$ denotes aggregate prefecture-level service price indexes for prefecture i at time t, $W_{i,j}$ is weights of CPI basket for prefecture i, subgroup, j (inflated so the weights sum up to one) and $P_{i,j,t}$ denotes subgroup-level price index data at the prefecture, which are adjusted for the effects of policy changes, such as consumption tax hikes, following Bank of Japan (2023). N denotes the number of subgroups. In constructing the index, we choose the subgroups that contain more than 80 percent of general services component.[3]

As for local labor costs, we use hourly wages (scheduled pay per hour) adjusted for labor productivity. The official prefectural wage statistics published by the Ministry of Health, Labour and Welfare are available only from 1997. To obtain long-term data series, we extend this data by linking prefecture-level wage data with alternative statistics published by the Ministry of Internal Affairs and Communication. With this approach, we extend the prefectural wage data backward to 1985. Prefecture-level labor productivity data is obtained from the R-JIP data published by the RIETI, the regional version of their comprehensive Japan Industry Productivity (JIP) database. As done by Boranova et al. (2021), we calculate trend labor productivity growth by applying the Hodrick-Prescott filter with the smoothing parameter λ=100 to the log-level of hourly real labor productivity data. Unit labor costs inflation ($ulc_{i,t}$), which control for labor productivity, can be expressed as follows,

$$ulc_{i,t} = w_{i,t} - LProd^{*}_{i,t}, \qquad (2)$$

where $w_{i,t}$ is the growth rate of hourly wage at prefecture i in period t and $LProd^{*}_{i,t}$ is the trend growth rate of hourly labor productivity at prefecture i in period t, obtained with the Hodrick-Prescott filter.

To control for local economic conditions that affect local labor costs and prices, we include a prefecture-level labor market tightness indicator, specifically the active job openings-to-applications ratio. This indicator captures the vacancy-to-unemployment rate

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[3] Relatedly, Kishaba and Okuda (2023) analyze prefecture-level service inflation, looking at subgroups with general service component of more than 50 percent. The main difference between our paper and their paper in terms of data is that we aggregate different subgroups to construct prefecture-level service index, while they only look at subgroup-level disaggregated data and do not analyze aggregate service index.

at the prefectural level, and we take the first difference of the indicator. Table 1 reports descriptive statistics of the prefecture-level data, as well as national import price inflation used in the empirical exercise. Figure 1 displays the indicators with time series of median values, as well as 10th and 90th percentile values.

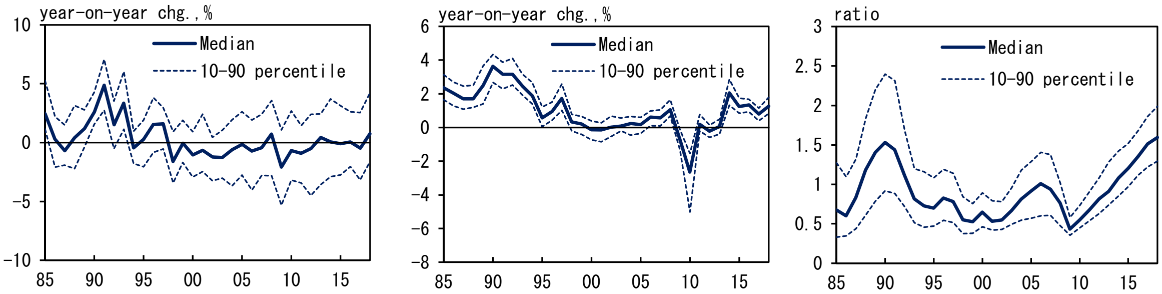
Table 1: Descriptive Statistics of Prefectural Data

		Unit Labor Cost (y-on-y change, %)	Services Price (y-on-y change, %)	Active Job Openings-to-Applicants Ratio	Import Price (y-on-y change, %)
Average	max	0.8	1.2	1.3	
	median	0.2	1.0	0.9	-1.1
	min	-0.4	0.7	0.4	
Std. Deviation	max	3.4	1.8	0.6	
	median	2.4	1.4	0.3	11.7
	min	1.8	1.1	0.2	

Note: In the table, max, median and minimum prefecture values in each subgroup are reported, for the sample from fiscal year 1985 to 2018. As the import price index is not available at the prefectural level, the country-level index is used for every prefecture.

Figure 1: Prefectural Data

Unit labor cost　Service price　Active job op.-to-app.



Note: In the panels, the mean, 10th and 90th percentile values at each point of time are shown. Average values of fiscal years.

2.2. Empirical framework

We rely on a panel vector autoregression model (PVAR) to analyze the linkage between wages and prices, utilizing prefectural panel data obtained in Section 2.1. The PVAR approach has been widely used in empirical studies, including on business cycles (e.g., Canova et al., 2007; Canova and Ciccarelli, 2013), monetary policy (e.g., Canova et al., 2012), macro-financial linkage (e.g., Love and Zicchino, 2006) and the impact of demographic trends (Aksoy et al., 2019).

The PVAR approach is suitable for our analysis on the dynamic linkage between labor costs and prices for the following points. First, as discussed in Canova and Ciccarelli

(2013), PVARs are suited to analyzing idiosyncratic shocks across particular units and time. In our context, shocks idiosyncratic to prefectures, which may be cancelled out at the aggregate level, can be utilized to analyze the linkage between labor costs and prices. Second, PVARs can be a powerful tool in analyzing the interdependencies of variables and their feedback effects within a particular unit. In our analysis, we examine the interaction among local labor costs, service prices, and labor market tightness at the prefectural level. As services are non-tradable and their prices are supposed to correspond to local economic conditions including labor costs, our PVAR model with prefectural data is suitable for shedding light on their relationship. Finally, PVARs can be used to estimate average effects across heterogeneous groups. By utilizing prefectural data, which has larger sample size, our model estimates the average relationship between labor costs and prices with respect to Japan.

The structure of our benchmark PVAR can be expressed as follows.

$$\begin{bmatrix} 1 & 0 & 0 \\ \alpha_0^{21} & 1 & 0 \\ \alpha_0^{31} & \alpha_0^{32} & 1 \end{bmatrix} \begin{bmatrix} ulc_{i,t} \\ \pi_{i,t} \\ u_{i,t} \end{bmatrix} = \sum_{l=1}^{L} \beta_l \begin{bmatrix} ulc_{i,t-l} \\ \pi_{i,t-l} \\ u_{i,t-l} \end{bmatrix} + \sum_{l=1}^{L} \begin{bmatrix} \gamma_l^1 \\ \gamma_l^2 \\ \gamma_l^3 \end{bmatrix} ipi_{t-l} + X_i + U_{i,t}, \quad (3)$$

where for a given prefecture i in period t, $ulc_{i,t}$ denotes unit labor cost inflation, which is defined in Equation (2) in Section 2.1 and can be calculated as wage growth adjusted for trend labor productivity growth at the prefectural level. $\pi_{i,t}$ is inflation for service items in prefecture i derived from price index in Equation (1) in Section 2.1, and $u_{i,t}$ denotes regional economic conditions (in this case, we use an annual change in the active job openings-to-applications ratio). β_l, 3×3 coefficient matrix, is the same among prefectures. The matrix X_{i} is a set of prefectural fixed effects, which captures time-invariant characteristics of prefectures. ipi_{t-l} is import price inflation, an exogenous variable in the system which controls for the effects of an import component of non-labor costs on price inflation. The matrix $U_{i,t}$ is a vector of unit-specific structural shocks that are assumed to be uncorrelated with one another. The lag length is denoted by L and is set to three, which is determined in favor of Bayesian Information Criterion. It is well known that the panel regression with lagged dependent variables cause a bias. To address this, we estimate parameters using Generalized Method of Moments proposed by Arellano and Bover (1995).[4]

[4] We use a Stata add-in developed by Abrigo and Love (2016).

Structural shocks are identified using Cholesky decomposition with the order of the variables shown above. By ordering labor cost growth before the other variables, this causal ordering assumes that labor costs are the most rigid variables in the system and are not affected contemporaneously by the shocks to prices and economic conditions (labor market tightness), but the shocks to labor costs can affect the other variables contemporaneously. This identification scheme is similar to previous studies such as Peneva and Rudd (2017), Bobeica et al. (2019), and Boranova et al. (2021). As discussed in Peneva and Rudd (2017), the shocks to labor cost growth in this identification scheme can be viewed as wage markup shocks given a prediction of structural models (Gali, 2011). For robustness, we also examine the alternative identification independent of the ordering of the variables. We use the annual sample from fiscal year 1985-2018 as a benchmark sample and analyze different sub-sample periods to estimate the change in the labor cost passthrough to prices.[5]

3. Benchmark Panel Vector Autoregression Model

3.1. Benchmark results: 1985-2018

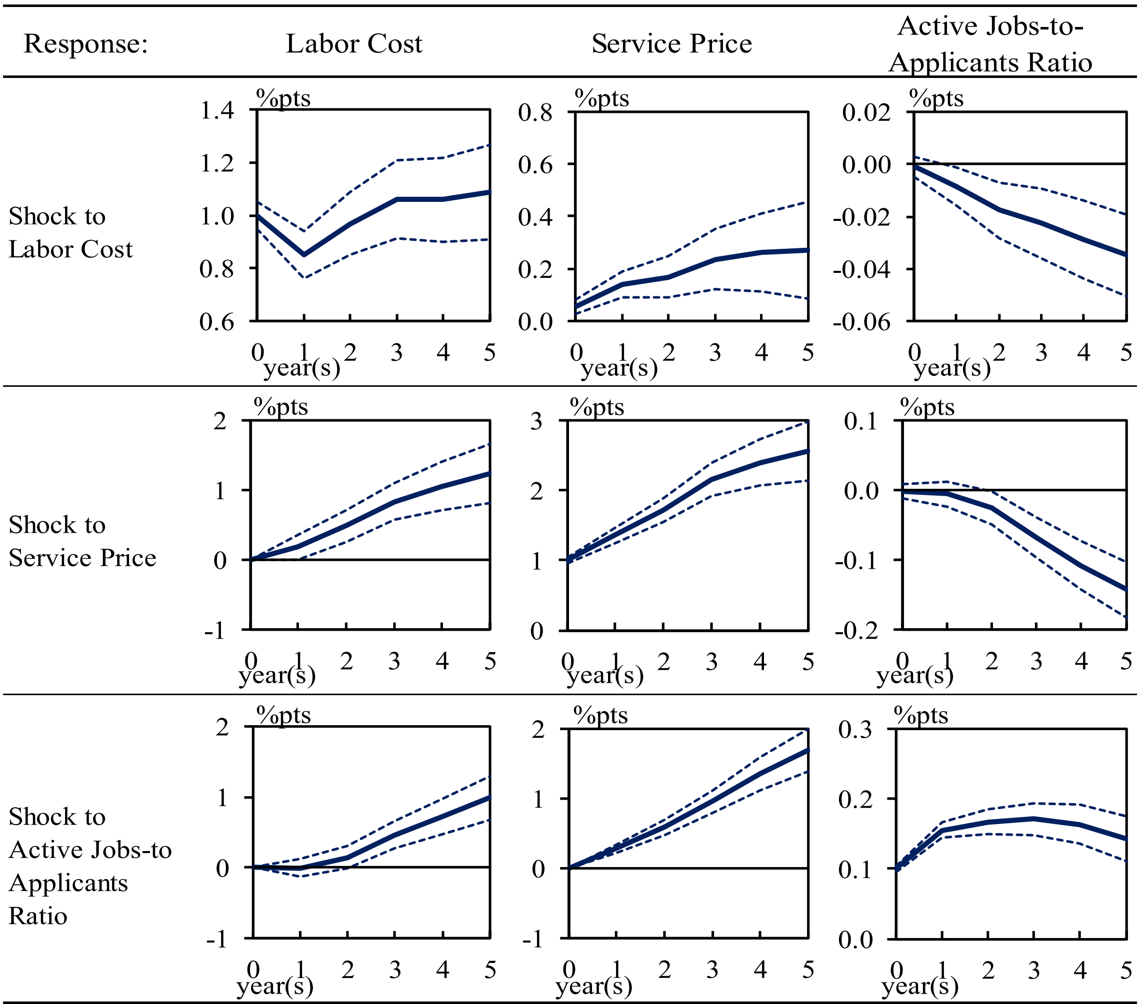
In this section, we present benchmark results using the prefectural data from fiscal year 1985-2018. Figure 2 shows the impulse responses of the endogenous variables to structural shocks identified by Cholesky decomposition. The first structural shock is scaled as a 1 percent increase in unit labor costs, the second structural shock is scaled as a 1 percent increase in service prices, and the third structural shock is scaled as a 0.1 percentage points increase in the active job openings-to-applications ratio. As shown in the first line, a structural shock to local labor costs leads to higher local inflation at the statistically significant levels, with a 1 percentage point labor cost shock causing a 0.14 percentage points of price inflation increase after one year, and 0.27 percentage points after five years. The shock also leads to a decline in the active job openings-to-applications ratio, suggesting a loosening of the local labor market conditions.

It is also worth mentioning how structural shocks to local service prices and labor market tightness affect the economic variables in the model, including unit labor costs. As shown in the second line, a structural shock to local service inflation significantly boosts local labor costs. A 1 percent shock to service prices has a statistically significant, yet relatively small impact on labor cost in the year, with an impact of 0.1 percent, but

[5] Fiscal year 2018 (ending March 2019) is the last data point below the pandemic. It should be noted that data endpoint is also constrained by availability of the R-JIP database, which we use for calculation of prefecture-level labor productivity.

the impact increases over time, with a cumulative impact of 1.2 percent after five years, while service prices also increase further along with the subsequent increase in labor costs. Regarding the structural shock to local labor market tightness, the tightening of labor market (an increase of job openings relative to applicants) causes the rise in prices and labor costs. The impact of the shock on labor costs is modest initially, but it has significant impact over the medium-term, as well as on service price inflation.

Figure 2: Impulse Response Functions: 1985-2018



Note: The chart shows cumulative impulse responses and the shock sizes are scaled at 1%pt for labor cost and service price and 0.1pt for the active job openings-to-applications ratio. The dotted lines are 99% confidence intervals generated from 1000 boot strapping. The model is discussed in Section 2.2. and Cholesky decomposition with the order of the variables shown in the chart is used for identification of the structural shocks. The sample period is from fiscal year 1985-2018.

To investigate passthrough of labor costs to prices, we calculate the passthrough ratio. À la Forbes et al. (2018), we calculate a shock-dependent passthrough ratio based on the cumulative impulse responses of local service price inflation and local labor cost inflation to structural shocks to unit labor costs. Specifically, the passthrough ratio is calculated as follows.

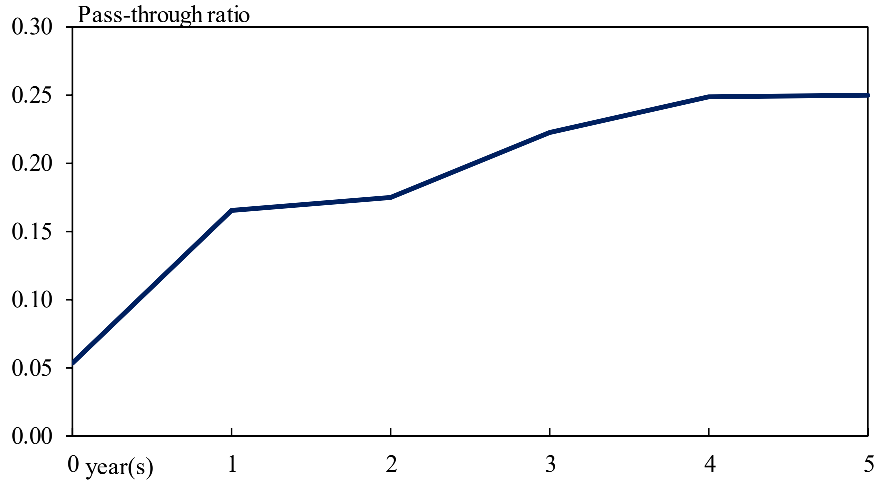
$$PT_h = \frac{CIRF(\pi)^h_{labor\ cost\ shock}}{CIRF(ulc)^h_{labor\ cost\ shock}} \ , \qquad (4)$$

where $CIRF(\pi)^h_{labor\ cost\ shock}$ is the cumulative impulse of price inflation π at horizon of h to a structural shock to unit labor costs, and $CIRF(ulc)^h_{labor\ cost\ shock}$ is that for unit labor cost inflation ulc.

Figure 3 shows the calculated passthrough ratio from the baseline result. Following some immediate impact on service price inflation, the passthrough ratio increases about 0.17 after two years and reaches around 0.25 after five years. The estimated passthrough is broadly similar to Heise et al. (2022), which analyze the U.S. industry-level data for 2003-2016. They find that the passthrough of labor costs to producer prices in the services sector reaches peak at 0.2 in two years, followed by a moderate decline to 0.15 in five years. Our result is also broadly similar to Peneva and Rudd (2017), which analyze time-varying responses of core inflation to Employment Cost Index-based trend labor cost growth in the U.S. using the time-varying parameter vector autoregression model with stochastic volatility. However, our passthrough is substantially lower than Ampudia et al. (2024), which analyze labor cost passthrough to producer prices using Euro area industry level data from 2009 to 2023. They find substantially larger passthrough, with passthrough reaching 0.5 in three years and higher passthrough for private services sector.[6]

[6] In addition to the differences in the sector coverage and the types of prices used for the analysis, a possible explanation for their relatively high passthrough is that their sample includes post-pandemic data. They find that passthrough increased after 2020, particularly in the private services sector.

Figure 3: Labor Cost Passthrough



Notes: The panel shows the labor cost passthrough ratio defined in Equation (4).

3.2. Subsample analysis

An important question is how the labor cost passthrough has evolved over time. Some studies show that passthrough varies over the time. As for the pre-pandemic studies, both Heise et al. (2022) and Peneva and Rudd (2017) point to a decline in labor cost passthrough in the U.S. For example, Heise et al. (2022) associate the decline in labor cost passthrough in the manufacturing sector with import competition and the rise in market concentration. Recently, Amiti et al. (2024) point to the reversal of the trend, arguing that the passthrough increased in the post-pandemic era. Regarding Japan's context, as discussed in Nishizaki et al. (2014) and Fukunaga et al. (2024a, 2024b), Japan faced different phases of inflation in the past decades, including a low-inflation period from mid-1990s, and this warrants examination of labor cost passthrough at different time periods.[7]

Against this background, in this subsection, we conduct a subsample analysis for the PVAR discussed in Section 2.2 to investigate the change in the degree of passthrough over the given period. Specifically, we change the starting point by five years from fiscal year 1985 to 2005, while keeping the endpoint of sample fixed at fiscal year 2018.[8] To ensure comparability, we fix the number of lags at three, same as the benchmark exercise.

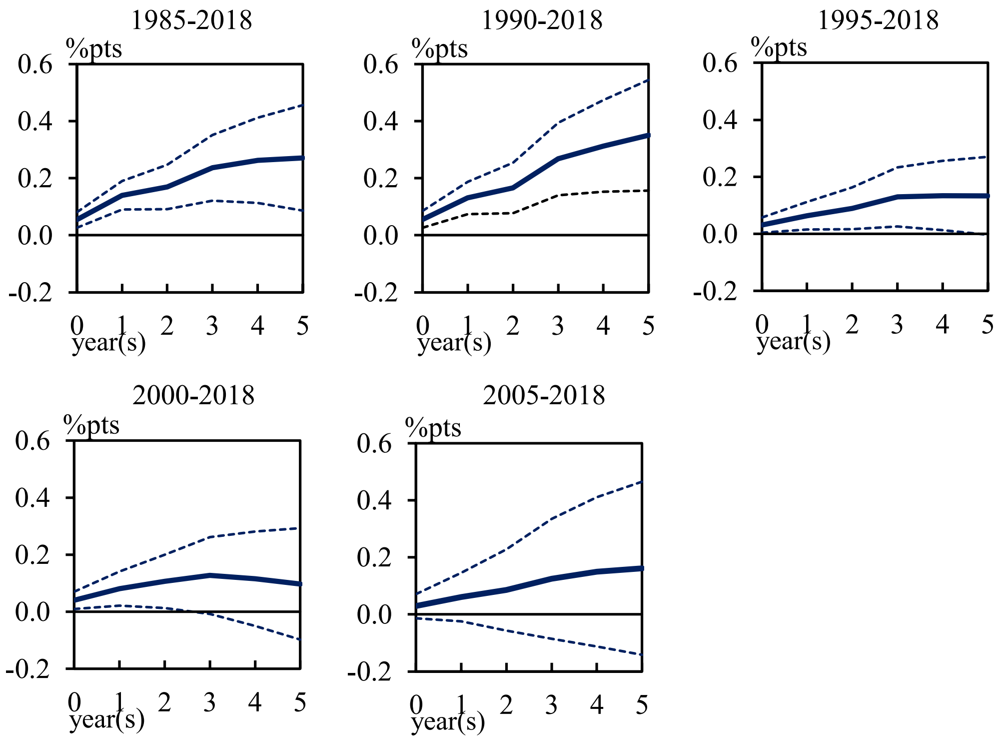
Figure 4 displays cumulative impulse response of service prices to 1 percent increase

[7] Relatedly, Nakamura et al. (2024) also analyze the drivers of Japan's inflation in the post-pandemic era. Using a dynamic factor model, Ueno (2024) finds that the trend components of wage and price inflation decoupled in late 1990s, before recoupling to some extent in the post-pandemic period.

[8] We take this approach rather than dividing the sample into two subsample periods given time series length.

in labor costs adjusted for productivity. It shows that service prices show relatively strong reaction to labor cost increase in the medium term for the sample periods starting from fiscal year 1985 and 1990, and the responses are statistically significant. By contrast, for the subsample starting from fiscal year 1995 or subsequent years, the responses of service prices to unit labor costs to weaken, and statistical significance of impulse response waning.

Figure 4: Impulse Response of Service Prices to an Increase in Labor Costs



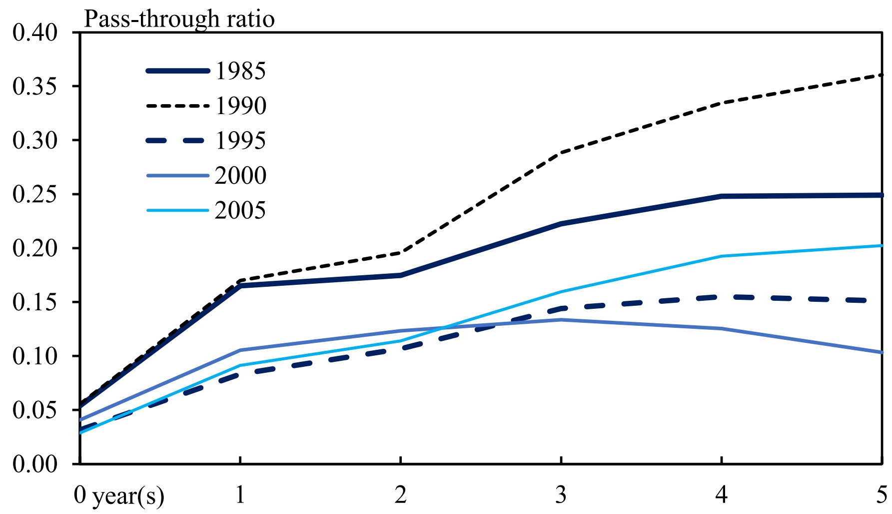
Note: The chart shows cumulative impulse responses of service prices to 1%pt increase in labor cost. The dotted lines are 99% confidence intervals generated from 1000 boot strapping. The model is discussed in Section 2.2. and Cholesky decomposition with the order of the variables shown in Figure 2 is used for identification of the structural shocks. Subsample analysis, with the data endpoint fixed at fiscal year 2018, is shown.

To take into account potential impact from the change in labor costs' own responses, we also calculate labor cost passthrough discussed in Section 3.1 for different subsample periods. Figure 5 suggests that the labor cost passthrough is consistently positive throughout all subsample periods. However, consistent with the changes in impulse responses, the degree of passthrough has weakened for the sample after the mid-1990s.[9]

[9] While it is not reported in the paper, the impulse response of labor cost inflation to service price inflation also weakened after the mid-1990s, and the impact became statistically insignificant.

In particular, the 1-year ahead passthrough ratio was around 0.15-0.2 in the subsample periods starting from fiscal year 1985 and 1990, but it declined to around 0.1 in the subsample period starting from 1995 or later. The decline in passthrough is also found in longer-term horizon.

Figure 5: Labor Cost Passthrough: Subsample Analysis



Notes: The panel shows the labor cost passthrough ratio defined in Equation (4). The legend shows the start year of subsample used for the passthrough calculation. The end of subsample is fixed at fiscal year 2018.

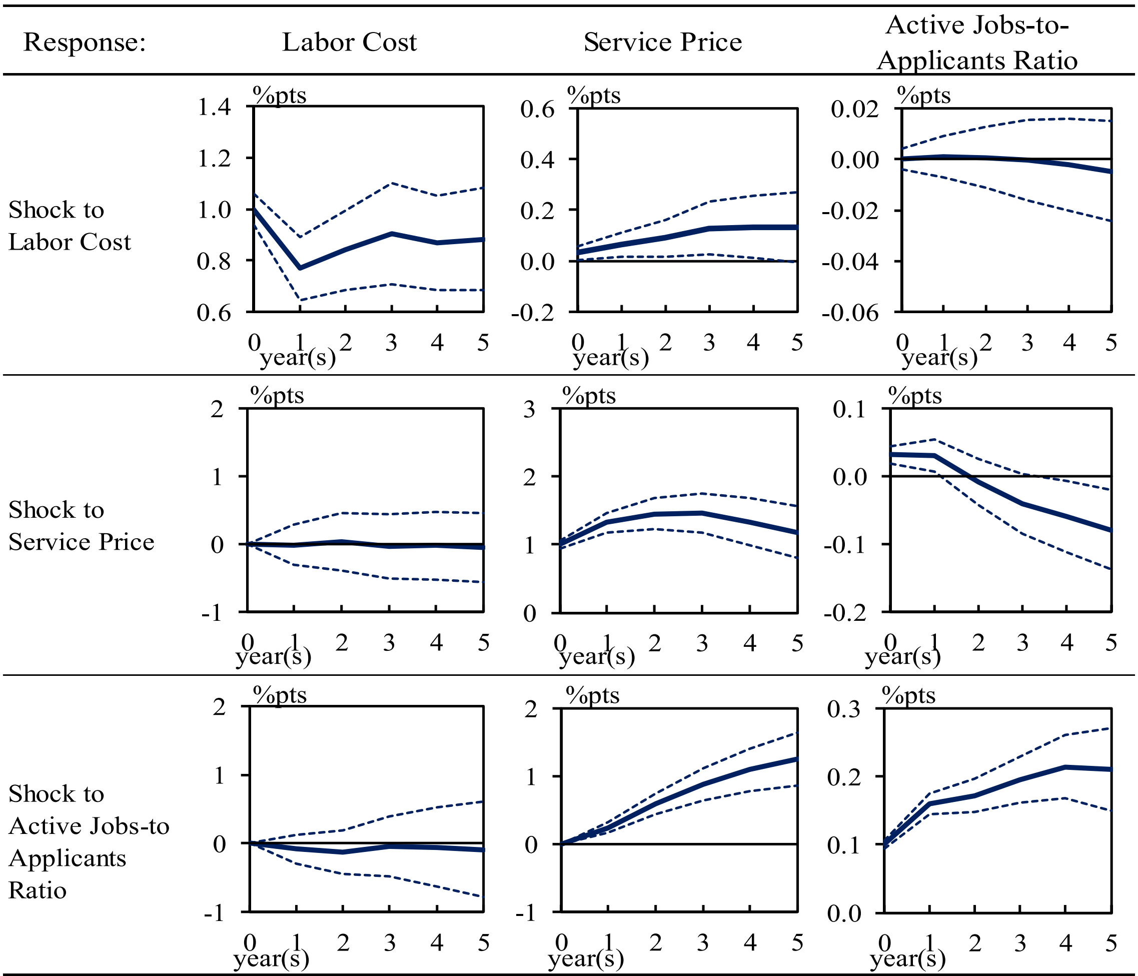
Both the subsample analysis for impulse response functions and the labor cost passthrough ratio indicate the weakening of linkage between labor costs and service prices from the mid-1990s.[10] This timing of change coincides with the U.S. evidence studied by Peneva and Rudd (2017), which find a decline of labor cost passthrough since the mid-1990s. More importantly, it aligns with the period when Japan entered low inflation phase (Fukunaga et al., 2024b). Our findings are also consistent with aggregate level analysis for Japan by Hoshi and Kashyap (2021), which identify disconnect between wage inflation and price inflation from the late 1990s. However, a key difference from their analysis is that our analysis using granular prefectural data finds statistically significant impulse responses of service prices to labor costs for the sample period starting from the mid-1990s or 2000s, albeit with weaker responsiveness of service prices. In contrast, their aggregate-level analysis does not find statistically significant impulse

[10] Related to this, Sasaki et al. (2024) estimate non-linear passthrough of input costs to Japan's consumer price inflation with a latent threshold model and find that wage passthrough to inflation tends to be larger when wage inflation is about above 4 percent, which was seen in the period until the early-1990s.

responses for the period starting from 1998. This suggests the importance of analyzing the nexus between labor costs and prices at a granular level.

Figure 6 presents impulse responses of the endogenous variables to the structural shocks, focusing on the subsample period after the mid-1990s (1995-2018), where a decline in labor cost passthrough became evident. In addition to the weakening of impulse response of service prices to labor costs, some notable changes compared to the full sample impulse response functions in Figure 2 are observed. First, unlike the full sample impulse responses based on 1985-2018, labor costs do not increase in response to a shock to service price inflation in this subsample period. This observation is consistent with Muto and Shintani (2020), which analyze the time varying parameter version of New Keynesian Wage Phillips Curve in Japan from 1970 to 2013 and find that the inflation indexation parameter followed downward trend over the subsample period and became statistically insignificant. As discussed in their paper, as well as in Fukunaga et al. (2023), a firm survey called "*Survey on Wage Increase*" conducted by the Ministry of Health, Labour and Welfare indicates that a higher share of Japanese firms viewed inflation rate as motivation for wage revisions in the 1970s and 1980s, but the share declined substantially by the late 1990s as Japan's inflation levels became low. In addition, for the post mid-1990s subsample period, labor costs became unresponsive to an increase in the active job openings-to-applications ratio, which is interpreted as tightening of local labor market conditions. This observation is broadly consistent with Muto and Shintani (2020), which find a flattening of New Keynesian Wage Phillips Curve in Japan from the late 1970s to early 2010s, although they find that the unemployment rate remains statistically significant at aggregate levels even for the post-1990s period. It is also possible that downward rigidities of nominal wage reduced wage adjustments after the mid-1990s period.

Figure 6: Impulse Response Functions: 1995-2018



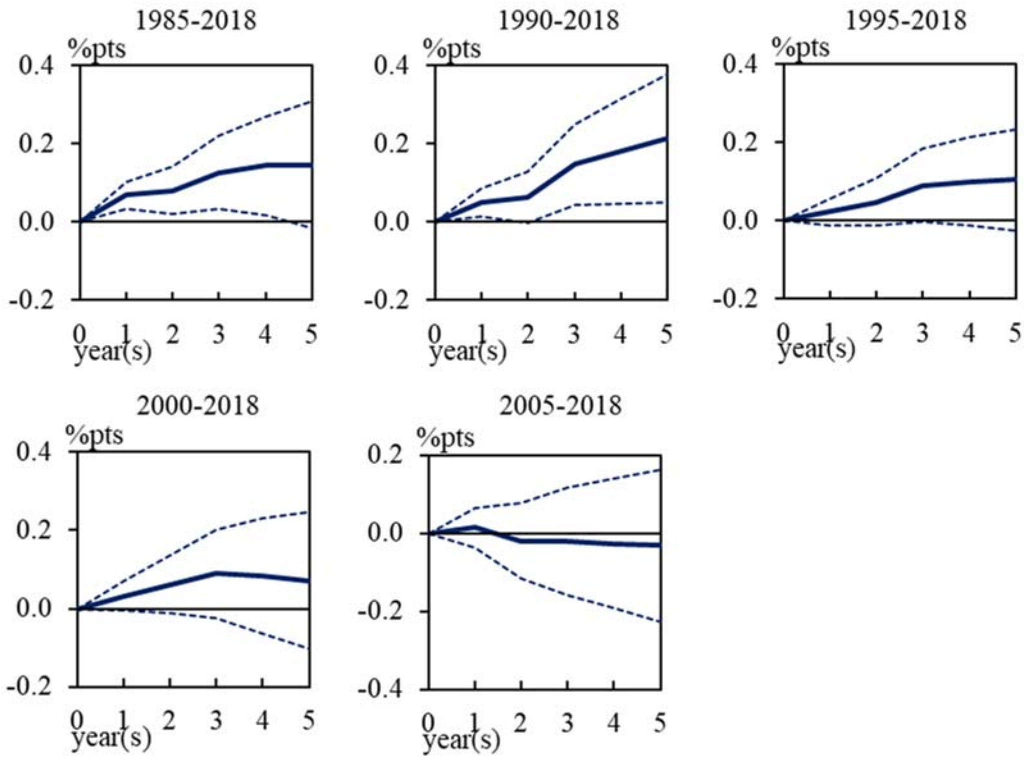
Note: The chart shows cumulative impulse responses and the shock sizes are scaled at 1%pt for labor cost and service price and 0.1pt for the active job openings-to-applications ratio. The dotted lines are 99% confidence intervals generated from 1000 boot strapping. The model is discussed in Section 2.2. and Cholesky decomposition with the order of the variables shown in the chart is used for identification of the structural shocks. The sample period is from fiscal year 1995-2018.

3.3. Robustness check

The benchmark result is based on Cholesky decomposition, with labor cost ordered before the other variables, similar to previous studies (e.g., Peneva and Rudd, 2017; Bobeica et al., 2019). As discussed in Peneva and Rudd (2017), the structural shock to labor costs can be interpreted as a wage markup shock. For robustness, we calculate the simple impulse response function for the PVAR model in this subsection, following Abrigo and Love (2016) and Jaeger and Paserman (2008), which generates impulse response functions independent from the ordering of variables. Specifically, the simple impulse response function assumes that, in the vector moving average representation, a shock to an endogenous variable does not cause a contemporaneous response of the other exogenous variables.

We examine whether a change in service prices' response to labor cost is also observed under this alternative identification. To ensure comparability, we run PVAR with the same specification as the pervious section and conduct subsample analysis with the alternative shock identification. Like in Section 3.2, we change the starting point by five years, from fiscal year 1985 to 2005, while keeping the endpoint of the sample fixed at fiscal year 2018. Figure 7 shows the impulse response of service price inflation to 1 percent increase in labor cost for different subsample periods. Similar to Cholesky identification, it is found that service price inflation became less responsive to labor costs, and the impulse response became statistically insignificant in the more recent subsample periods.

Figure 7: Simple Impulse Response Functions:
Impulse Response of Service Prices to an Increase in Labor Costs



Note: The chart shows cumulative impulse responses of service prices to 1%pt increase in labor costs, based on the panel VAR model discussed in Section 2.2. Simple impulse response functions, which are independent of the ordering of the variables, is reported. The dotted lines are 99% confidence intervals generated from 1000 boot strapping. The chart shows subsample analysis, with the data endpoint fixed at fiscal year 2018.

4. Extended Analysis: industry-prefecture level analysis

The previous section discussed the wage-price nexus with prefectural data and presented evidence that labor cost passthrough to price inflation weakened in the pre-pandemic period after the mid-1990s. In this section, utilizing industry-prefecture level data, we further investigate whether labor cost passthrough to value added deflators changed in Japan after the mid-1990s, when Japan entered the low inflation environment. Additionally, we investigate whether asymmetric labor cost passthrough exists.

4.1. Industry-prefectural dataset (R-JIP database)

In this section, we investigate labor cost passthrough further by utilizing the R-JIP database compiled by the RIETI, Japan.[11] The R-JIP database offers annual industry-prefectural data for variables including labor costs and deflators, and provides even more granular information for analyzing labor cost passthrough. In addition, while we exclude goods inflation in the previous section to isolate impacts of inter-prefectural trades, labor cost passthrough for the manufacturing sector can be analyzed in this database as industry-prefecture level deflators for their value added are included. The database has been widely used in empirical research, such as studies by Imai (2022) and Akesaka and Kikuchi (2024).

To analyze a change in labor cost passthrough over time, we use both the latest version of the R-JIP (R-JIP 2021), which is available for the period 1994-2018, and the vintage version (R-JIP 2017), which is available from 1970-2012. While combining the two versions of dataset at subcomponent levels is not feasible due to the methodological change in System of National Accounts, a change in labor cost passthrough can be investigated by analyzing the two version of dataset separately.

4.2. Empirical approach and results

While the previous section used panel vector autoregression, we adopt a simpler regression approach in this section, similar to Heise et al. (2022), given relatively short time series length of the data and necessity to account for different levels of labor share across industries. As discussed in the next subsection, it is relatively straightforward to extend this regression model to analyze potential asymmetric effects. Our benchmark specification can be expressed as following:

$$\Delta_{t-h,t} \ln\left(P_{i,j,t}\right) = \beta_h LS_{i,j,t} * \Delta_{t-h,t} \ln\left(w_{i,j,t}\right) + \alpha_i + \delta_j + \eta_t + \varepsilon_{i,j,t} \quad (5)$$

where $P_{i,j,t}$ denotes a value-added deflator for prefecture i, industry j, at time t, $LS_{i,j,t}$ denotes industry-prefecture specific labor share (the ratio of total labor costs-to-nominal value added), $w_{i,j,t}$ denotes hourly labor costs. In addition, α_i, δ_j, and η_t are

[11] Tokui and Makino (2022) discuss methodological details about the R-JIP data.

time-invariant prefectural fixed effects, time-invariant industry fixed effects, and time fixed effects which controls for macroeconomic developments, respectively.[12] In the specification above, β_h is the coefficient of our interest, which captures passthrough of labor costs to value added deflators, adjusted for labor share. h is the duration we analyze to labor cost passthrough. We calculate Driscoll-Kraay standard errors (Driscoll and Kraay, 1998) with the lag length of three years to account for cross-sectional and time series correlation in the errors.

As in the previous section, we aim to analyze the change in labor cost passthrough over time. Given that the latest version of the R-JIP (R-JIP 2021), consistent with System of National Account 2008, is available only for the period 1994-2018, we also use the vintage version of the R-JIP (R-JIP 2017) to analyze how labor cost passthrough before the mid-1990s is different from that in subsequent periods. To address outliers, we trim values below 1 percentile and above 99 percentiles of the variables for both databases before running the panel regression.

Another important consideration is that there may be heterogeneity in the degree of labor cost passthrough across different industries. To account for potential heterogeneity, we estimate the services and manufacturing industry sector separately in this section. Specifically, we include 9 industries (5 industries in R-JIP 2017) for the services sector and 14 industries (13 industries in R-JIP 2017) for the manufacturing sector (see Appendix II for details).

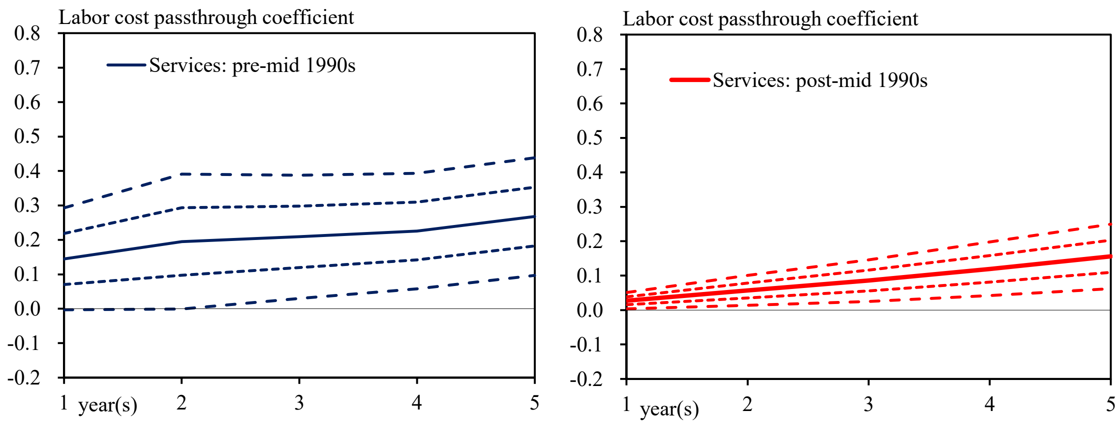
Figure 8 shows the estimated labor share-adjusted labor cost passthrough coefficient (β_h) for the services sector at different time horizon. As discussed earlier, given data availability, we calculate passthrough from 1994-2018 using the 2021 version of R-JIP database (available from 1994-2018). Additionally, for comparison, we calculate passthrough for the pre-mid 1990s period, specifically 1972-1993, using the 2017 version of the R-JIP (available from 1970-2012).[13] Consistent with the previous section, the subsample analysis suggests that labor cost passthrough declined for the period after the mid-1990s compared to the earlier subsample period. While the estimated labor cost passthrough for the post mid-1990s is low, it is positive and statistically significant. Figure

[12] While trend labor productivity is not explicitly controlled in this regression, sector-wide labor productivity trend is controlled by time fixed effects, and prefecture and industry fixed effects. As discussed below and reported in Appendix III, we run robustness checks using alternative specifications that include labor quality-adjusted labor costs and total factor productivity.

[13] While R-JIP 2017 is available from 1970, we use the data from 1972 due to significant missing observations in the first two years.

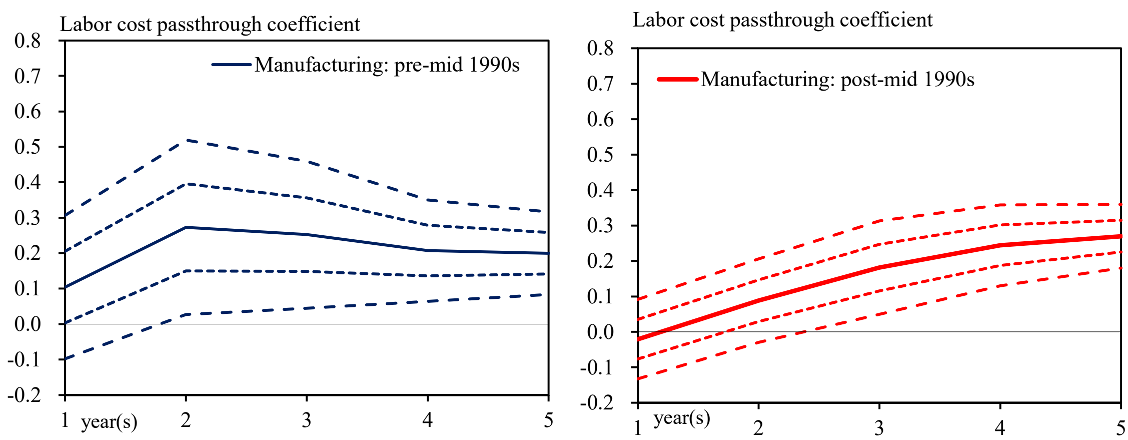
9 displays the labor cost passthrough coefficient (β_h) for manufacturing industry. Similar to the services sector, we find a decline in labor cost passthrough for the subsample period after the mid-1990s (i.e. 1994-2018), while labor cost passthrough remains statistically significant for the subsample period. Compared to the services sector, the decline in labor cost passthrough in the manufacturing sector is more pronounced in the near-term horizon.

Figure 8: Labor Cost Passthrough: The Services Sector



Notes: The left panel shows labor share-adjusted labor cost passthrough to value added deflators for services industries for the pre-mid 1990s period (1972-1993) calculated from the R-JIP 2017 database based on Equation (5). The right panel shows same calculation for the post-mid 1990s period (1994-2018) using the R-JIP 2021 database. Dash lines show 1 and 2 Driscoll-Kraay standard errors bands.

Figure 9: Labor Cost Passthrough: The Manufacturing Sector



Notes: The left panel shows labor share-adjusted labor cost passthrough to value added deflators for manufacturing industries for the pre-mid 1990s period (1972-1993) calculated from the R-JIP 2017 database based on Equation (5). The right panel shows same calculation for the post-mid 1990s period (1994-2018) using the R-JIP 2021 database. Dash lines show 1 and 2 Driscoll-Kraay standard errors bands.

For robustness checks, we also estimate alternative specifications. The first specification uses labor quality-adjusted hourly labor costs, which is derived by dividing hourly labor costs by labor quality data available in the R-JIP database, instead of simple hourly labor costs. As done in Equation (5), we convert labor quality-adjusted hourly labor costs to growth rate and multiply them by industry-prefecture-specific labor share. The second specification includes the growth rates of industry-prefecture specific total factor productivity for the same horizon, in addition to hourly labor costs in Equation (6). These results are reported in Appendix III.[14] Overall, the results are robust for the alternative specifications.

4.3. Asymmetric analysis

In the previous exercise, we assumed that labor cost passthrough is symmetric. In this subsection, we extend Equation (5) to investigate potential asymmetric passthrough, comparing the pre-mid 1990s period to the post-mid-1990s period. In the passthrough literature, especially in the context of oil and exchange rate passthrough to inflation, many studies confirm the *rockets and feathers effect*, a phenomenon in which prices increase faster than they fall (e.g., Tappata, 2009 and references therein). Relatedly, Ball and Mankiw (1994) consider a menu-cost model and argue that it is optimal for firms to respond more strongly to positive shocks to prices when trend inflation is positive. This theoretical prediction suggests potential changes in asymmetric passthrough patterns in Japan along with a change in trend inflation. To analyze potential asymmetric labor cost passthrough, we run the following regression, which incorporates the non-linear specification of Shin et al. (2014):

$$\Delta_{t-h,t}\ln\left(P_{i,j,t}\right) = \beta_h^{+} LS_{i,j,t} * S_{h,t}^{+} + \beta_h^{-} LS_{i,j,t} * S_{h,t}^{-} + \alpha_i + \delta_j + \eta_t + \varepsilon_{i,j,t}, \quad (6)$$

where

$$S_{h,t}^{+} = \Sigma_{k=0}^{h-1}\max(0, \Delta\ln\left(w_{i,j,t-k}\right)) \text{ and}$$
$$S_{h,t}^{-} = \Sigma_{k=0}^{h-1}\min(0, \Delta\ln\left(w_{i,j,t-k}\right)).$$

In the specification above, $S_{h,t}^{+}$ captures the cumulative value of positive labor cost growth rates for the horizon h and $S_{h,t}^{-}$ captures the cumulative value of negative labor cost growth rates for the same period. In this equation, β_h^{+} captures labor cost passthrough when labor costs increase, and β_h^{-} captures passthrough when labor costs decline. We estimate the equation for the services and manufacturing sectors separately and ask if there is a difference between the upward and downward passthrough coefficients.

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[14] To conserve a space, we report the result for two-year cumulative changes and five-year cumulative changes.

Table 2 reports asymmetric labor cost parameters in Equation 6 for the manufacturing and services sectors in both pre- and post-mid-1990s periods, as well as the results of Wald tests for the asymmetric parameters (i.e., $\beta_h^+ = \beta_h^-$). In the pre-mid-1990s period, we find statistically significant asymmetric labor cost passthrough in the services sector, with upward passthrough stronger than downward passthrough, consistent with the literature. The estimated upward passthrough coefficients for the manufacturing sector are also larger than the corresponding downward coefficients, but the differences are not statistically significant. Conversely, in the post-mid-1990s period, such a *rockets and feathers effect* are not found. The estimation suggests that, for that period, downward passthrough in the services sector tends to be larger over 5-year horizon. We also observe larger downward labor cost passthrough parameters for the manufacturing sector in the post-mid 1990s period, although the differences from the upward parameters are not statistically significant.

Table 2: Asymmetric Labor Cost Passthrough (β_h^+, β_h^-, and β_h^+-β_h^-)

			h=1	h=2	h=3	h=4	h=5
Svcs.	Pre-mid 90s	up	0.2051**	0.2442**	0.2512**	0.2612***	0.3004***
		down	-0.2252**	-0.1372*	-0.0507	0.0019	0.0691
		diff.	0.4303**	0.3814*	0.3020**	0.2593***	0.2313***
	Post-mid 90s	up	0.0218	0.0416**	0.0641***	0.0905***	0.1186***
		down	0.0331	0.0753**	0.1128**	0.1575**	0.2061***
		diff.	-0.0112	-0.0337	-0.0487	-0.0670	-0.0875**
Mfg.	Pre-mid 90s	up	0.1092	0.2874**	0.2589**	0.2128***	0.2032***
		down	0.0229	-0.0425	0.0433	-0.0284	-0.0516
		diff.	0.0864	0.3300	0.2156	0.2412	0.2548
	Post-mid 90s	up	-0.0706	0.0212	0.0985	0.1629***	0.1895***
		down	-0.0359	0.16256	0.2765*	0.3398**	0.3664***
		diff.	-0.1066	-0.1414	-0.1780	-0.1769	-0.1769

Notes: The table shows upward labor share-adjusted labor cost passthrough parameters (β_h^+) and downward labor share-adjusted labor cost passthrough parameters (β_h^-) for the services and manufacturing sectors based on Equation (6), as well as their differences ($\beta_h^+ - \beta_h^-$). ***, ** and * denote 1 percent, 5 percent and 10 percent statistical significance levels, respectively. Driscoll-Kraay standard errors are calculated. Pre-mid 90s covers 1972-1993 and the estimation is based on R-JIP 2017. Post-mid 90s covers 1994-2018 and the estimation is based on R-JIP 2021.

4.4. Discussion of the results

The industry-prefecture level analysis suggests that labor cost passthrough declined after the mid-1990s for both the services and manufacturing sectors, consistent with prefectural level analysis. This is similar to that of Heise et al. (2022), which analyze the U.S. pre-pandemic long-term data and find a decline in labor cost-passthrough to consumer price inflation and producer price inflation. There are several theories that suggest a decline in passthrough when trend inflation is low. For example, Taylor (2000) argues that price and wage setting behaviors can weaken under low-inflationary environment due to expectation channels. Devereux and Yetman (2010) also develop a theoretical model that allows frequency of price changes to be endogenous and predict that exchange rate passthrough is increasing with average inflation, but at a declining rate. In this regard, Okimoto (2019) points to a shift to a low trend inflation regime in Japan in the mid-1990s, and Kaihatsu and Nakajima (2018) also find a decline in Japan's trend inflation in the mid-1990s.

Comparing the services and manufacturing sectors, the decline in labor cost passthrough is more pronounced in the manufacturing sector in the near term. This observation is consistent with the study for the U.S. industries by Heise et al. (2022). Their theoretical model predicts that an increased import competition and a rise in market concentration in the manufacturing sector reduced labor cost passthrough. In this regard, as discussed in Hogen et al. (2024) and references therein, import penetration in Japan has increased steadily since the mid-1990s. Regarding market concentration, Kikuchi (2024) analyzes market concentration in Japan since 1980 using the establishment-level data from the Census of Manufacture and the Basic Survey of Japanese Business Structure and Activities and points to an increase in market concentration in Japan both at national and local levels since the mid-1990s, including in manufacturing sector. Collectively, these studies suggest a decline in labor cost passthrough in manufacturing sector in Japan.

In the asymmetric exercise, we find the evidence of the *rockets and feathers effect*— stronger upward passthrough and weaker downward passthrough— in the services sector for the pre-mid 1990s period, while such asymmetric effects are not observed in the post-mid-1990s period. In this regard, Ball and Mankiw (1994) develop a menu-cost model in which positive trend inflation causes firms' relative prices to decline automatically. In their model, shocks that raise firms' desired prices trigger larger price responses compared to shocks that lower desired prices.[15] It is possible that the decline in trend inflation in the post-mid 1990s period led to the disappearance of asymmetric passthrough. This also implies that asymmetric effects intensify when trend inflation picks up.

5. Conclusion

[15] When a firm wants a lower relative price, it does not need to pay the menu cost to do so as positive trend inflation automatically lower the relative price.

In this paper, we analyze the nexus between labor costs and prices in the pre-pandemic period in Japan, including labor cost passthrough to prices, utilizing novel long-term subnational datasets. In the first part of the paper, we construct a long-term prefectural dataset of productivity-adjusted labor costs, service prices and local labor market tightness, utilizing relevant disaggregate prefectural data and apply prefecture-level Panel Vector Autoregression to study the interlinkages of the variables. We find statistically significant labor cost passthrough to service prices at local level for the sample of fiscal year 1985-2018, but also find that the passthrough weakened for the sample after the mid-1990s, where Japan entered low inflation phase. In addition, by utilizing the industry-prefecture data, we find that both the services and manufacturing sectors experienced a decline in labor cost passthrough to value added deflator after the mid-1990s. We find statistically significant asymmetric labor cost passthrough in the services sector for the period before the mid-1990s, characterized by larger upward passthrough compared to downward passthrough, but such asymmetric effects disappeared in the post-mid 1990s period.

While our paper focuses on pre-pandemic data due to the availability of subnational data, many studies point to significant changes in inflation dynamics, as well as labor market developments in the post-pandemic era, both globally and in Japan, which warrants re-examination of labor cost passthrough. We offer evidence of structural changes in labor cost passthrough in the post-mid 1990s period, and this may be linked to factors including trend inflation. Thus, it is possible that labor cost passthrough has intensified in the post-pandemic era, which we do not study in this paper. The evaluation of potential changes in labor cost passthrough in the post-pandemic period constitutes an area for future research and should be undertaken in conjunction with the ongoing accumulation of subnational data.

Another potential area for future research in the context of Japan is to incorporate the dual structure of Japanese labor market in the analysis of labor cost passthrough, which is not explicitly considered in our paper. Globally, dual structural of labor markets attract increasing attention (e.g., Ahn et al., 2023), and it has been increasing and prominent feature of Japanese labor market (e.g., Fukunaga et al., 2023, Date et al., 2024, Nakamura et al., 2024 and Furukawa et al., 2025).

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Appendix I. Construction of prefectural dataset

This appendix discusses the data used to construct prefectural database discussed in Section 2 and used in Section 3.

A1.1 Service prices

As discussed in Section 2, we focus on non-tradable service component of consumer price data in preparing prefectural dataset. Complication in constructing prefecture level service price data is that the service price index is published only at the country-level and not available at the prefectural level. To deal with this limitation, we construct prefectural-level service index based on prefectures' subgroup-level indexes. As subgroup level data include goods component, general service component and public service component, we select categories that include general service component of more than 80 percent, which narrows down to the seven categories shown in Table A1.[16] Importantly, we do not include administrative items and housing rents as they may be largely influenced by non-cyclical factors.

As expressed in Equation (1), we then use prefecture-specific weights to calculate weighted average service price inflation for 47 prefectures. The country-level service inflation constructed with this criterion moves similarly to the country-level general service inflation. The impact of consumption taxes is adjusted based on Bank of Japan's calculation.

Table A1: Subgroup Level Data Used to Construct Prefecture Level Service Prices

Subgroup	**Share of General Services**	**Weights**
Personal care services	100	1.1
Tutorial fees	100	0.8
Services related to clothing	100	0.2
Meals outside the home	94.6	4.6
School fees	85.5	2.1
Recreational services	83.7	5.2
Domestic services	82.1	0.3

Notes: The share of general services is the country-level data. Weights are in terms of all items and are country-level data.

[16] We use the country-level weights to select subgroups, which makes prefecture-level service inflation comparable across prefectures. While country-level weights are shown in Table A1, prefecture-specific weights are used for constructing prefecture-level service prices.

A1.2 Productivity-adjusted labor costs

We combine two different data sources to construct long-term wage data. The *Basic Survey on Wage Structure*, the main source for wage inflation, only dates back to 1997. In order to extend the sample period, we use alternative sources of data, *Social Indicators by Prefecture* published annually by Ministry of Internal Affairs and Communications for the period prior to 1997. We use regular wages and hours worked by sex to calculate hourly wages by sex, and calculate weighted average data using the weights of employment by sex.

To calculate productivity-adjusted labor costs, we calculate prefecture-level real hourly labor productivity based on the R-JIP database (R-JIP 2017 and R-JIP 2021) compiled by Research Institute of Economy, Trade and Industry (RIETI). We apply Hodrick-Prescott filter with the smoothing parameter λ=100 to logarithm level data and calculate trend growth rates. It should be noted that the prefectural-level labor productivity data is available in calendar year basis, while the other prefectural data are in fiscal year basis. The impact of this discrepancy should be minimal as we use smoother filtered data rather than raw data, and there is a significant overlap (9 months) between calendar year and fiscal year.

A1.3 Local labor market tightness

As discussed in Section 2.2, we use the active job openings-to-applications ratio (*yuko kyujin bairitsu*) for local labor market tightness. The prefecture-level data of this indicator is obtained from Ministry of Health, Labour and Welfare. The active job openings-to-applications ratio is widely used as an indicator for labor market tightness in previous studies on Japan such as Kondo (2007), and Kondo and Shoji (2019).

Appendix II. Industry-Prefecture dataset

As for industry-prefecture analysis, we analyze the pre-mid-1990s period (1972-1993) and post-mid-1990s period (1994-2018) using R-JIP 2017 and R-JIP 2021 databases compiled by Research Institute of Economy, Trade and Industry (RIETI), respectively. The two databases have different industry classifications. We choose industry codes to cover the manufacturing and services sectors.

A2.1 R-JIP 2021

We use the R-JIP 2021 database (available from 1994-2018) for the post-mid-1990s period. In this database, we include the following 14 industries as the manufacturing sector (industry code: 3-16): Food products; Textile products; Pulp, paper, and paper products; Chemical, petroleum, and coal products; Ceramic, stone, and clay products; Primary metals; Fabricated metal products; General-purpose, production, and business machinery; Electronic components and devices; Electrical machinery; Information and communication equipment; Transportation machinery; Printing industry; Other manufacturing industries. For the services sector, we include the following 9 industries for the services sector (industry code: 19-27): Wholesale trade; Retail trade; Transportation and postal services; Accommodation and food services; Telecommunications and broadcasting; Information services and media production; Finance and insurance; Real estate; Professional, scientific, and technical services.

A2.2 R-JIP 2017

We use the R-JIP 2017 database (available from 1970-2012) for the pre-mid-1990s period. In this database, we include the following 13 industries as the manufacturing sector (industry code: 3-15): Food products; Textiles; Pulp and paper; Chemicals; Petroleum and coal products; Ceramic, stone, and clay products; Primary metals; Metal products; General machinery; Electrical machinery; Transportation machinery; Precision machinery; Other manufacturing industries. For the services sector, we include the following 5 industries for the services sector (industry code: 18-22): Wholesale and retail Trade; Finance and insurance; Real estate； Transportation and communications; Services (Private, Non-profit).

Appendix III. Additional results of industry-prefecture analysis

Table A3.1 Labor cost passthrough: the pre-mid-1990s, the services sector

	h=2			h=5		
	(1)	(2)	(3)	(4)	(5)	(6)
LS × Δ LC	0.1951*	0.2018**		0.2675***	0.1912**	
	(0.0979)	(0.0928)		(0.0854)	(0.0866)	
Δ TFP		-0.2127***			-0.2472***	
		(0.0388)			(0.0346)	
LS × Δ LQC			0.1752*			0.2845**
			(0.0935)			(0.0974)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.6551	0.702	0.6508	0.8298	0.874	0.8299
Observations	4007	4007	4007	3559	3559	3559
Years	1972-1993	1972-1993	1972-1993	1972-1993	1972-1993	1972-1993

Notes: The table shows labor share-adjusted labor cost passthrough to value added deflators for services industries for the pre-mid 1990s period (1972-1993) calculated from the R-JIP 2017 database based on Equation (5). Dependent variable is the cumulative change in services industry value added deflators, and *h* is the length of duration. *LS* denotes labor share, *LC* denotes labor costs, and *LQC* denotes labor quality-adjusted labor costs. Numbers in parentheses are Driscoll-Kraay standard errors with lag of three years. ***, ** and * show 1 percent, 5 percent, and 10 percent statistical significance, respectively.

Table A3.2 Labor cost passthrough: the post-mid-1990s, the services sector

	h=2			h=5		
	(1)	(2)	(3)	(4)	(5)	(6)
LS × Δ LC	0.0570**	0.0649***		0.1561***	0.1706***	
	(0.0217)	(0.0196)		(0.0468)	(0.0446)	
Δ TFP		-0.0444**			-0.0638	
		(0.0214)			(0.0380)	
LS × Δ LQC			0.0295			0.1192**
			(0.0301)			(0.0533)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.3750	0.3892	0.3722	0.4606	0.4698	0.4555
Observations	9412	9412	9412	8330	8330	8330
Years	1994-2018	1994-2018	1994-2018	1994-2018	1994-2018	1994-2018

Notes: The table shows labor share-adjusted labor cost passthrough to value added deflators for services industries for the post-mid 1990s period (1994-2018) calculated from the R-JIP 2021 database based on Equation (5). Dependent variable is the cumulative change in services industry value added deflators, and *h* is the length of duration. *LS* denotes labor share, *LC* denotes labor costs, and *LQC* denotes labor quality-adjusted labor costs. Numbers in parentheses are Driscoll-Kraay standard errors with lag of three years. ***, ** and * show 1 percent, 5 percent, and 10 percent statistical significance, respectively.

Table A3.3 Labor cost passthrough: the pre-mid-1990s, the manufacturing sector

	h=2			h=5		
	(1)	(2)	(3)	(4)	(5)	(6)
LS × Δ LC	0.2730**	0.2571**		0.1997***	0.1883***	
	(0.1230)	(0.1153)		(0.0583)	(0.0612)	
Δ TFP		-0.0192			-0.0106	
		(0.0131)			(0.0062)	
LS × Δ LQC			0.2438**			0.2314***
			(0.0935)			(0.0974)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.4692	0.4755	0.4694	0.7504	0.7523	0.7515
Observations	10306	10306	10306	8976	8976	8976
Years	1972-1993	1972-1993	1972-1993	1972-1993	1972-1993	1972-1993

Notes: The table shows labor share-adjusted labor cost passthrough to value added deflators for manufacturing industries for the pre-mid 1990s period (1972-1993) calculated from the R-JIP 2017 database based on Equation (5). Dependent variable is the cumulative change in value added deflators, and *h* is the length of duration. *LS* denotes labor share, *LC* denotes labor costs, and *LQC* denotes labor quality-adjusted labor costs. Numbers in parentheses are Driscoll-Kraay standard errors with lag of three years. ***, ** and * show 1 percent, 5 percent, and 10 percent statistical significance, respectively.

Table A3.4 Labor cost passthrough: the post-mid-1990s, the manufacturing sector

	h=2			h=5		
	(1)	(2)	(3)	(4)	(5)	(6)
LS × Δ LC	0.0881	0.0835		0.2670***	0.2474***	
	(0.0589)	(0.0583)		(0.0449)	(0.0470)	
Δ TFP		-0.0380**			-0.0715***	
		(0.0047)			(0.0112)	
LS × Δ LQC			0.0867**			0.2494**
			(0.0346)			(0.0573)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5931	0.6052	0.5937	0.7530	0.7670	0.7529
Observations	13577	13570	13577	11756	11749	11756
Years	1994-2018	1994-2018	1994-2018	1994-2018	1994-2018	1994-2018

Notes: The table shows labor share-adjusted labor cost passthrough to value added deflators for manufacturing industries for the post-mid 1990s period (1994-2018) calculated from the R-JIP 2021 database based on Equation (5). Dependent variable is the cumulative change in manufacturing industry value added deflators, and *h* is the length of duration. *LS* denotes labor share, *LC* denotes labor costs, and *LQC* denotes labor quality-adjusted labor costs. Numbers in parentheses are Driscoll-Kraay standard errors with lag of three years. ***, ** and * show 1 percent, 5 percent, and 10 percent statistical significance, respectively.