The Missing Inflation Puzzle: The Role of the Wage-Price Pass-Through*

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Abstract

Price inflation in the U.S. has been sluggish and slow to pick up in the last two decades. We show that this missing inflation can be traced to a growing disconnect between unemployment and core goods inflation. We exploit rich industry-level data to show that weakening pass-through from wages to prices in the goods-producing sector is an important source of the slow inflation pick-up in the last two decades. We set up a theoretical framework where markups and pass-through are a function of firms' market shares and show that increased import competition and rising market concentration reduce pass-through from wages to prices. We then use industry-level data and find strong support for these two channels consistent with the implications of our model.

Keywords: Inflation dynamics, Phillips curve, pass-through, import competition, market concentration
JEL Classification: E24, E31

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1 Introduction

Price inflation in the U.S. has remained sluggish and below the Federal Reserve's inflation target of 2% during the decade-long expansion following the Great Recession. This behavior of price inflation has been considered puzzling by many policymakers and academics especially given that the unemployment rate stood at 3.5% at the end of 2019—its lowest level in almost half a century.[1] In this paper, we revisit this growing disconnect between unemployment and inflation and show that declining pass-through from wages to prices in the goods-producing sector has been an important source of the slow inflation pick-up. We attribute the decline in pass-through to rising import competition and increased market concentration and provide strong empirical support for these two channels using rich industry-level data. We also show that the two explanations are consistent with the predictions of a theoretical framework in which markups and pass-through are a function of firms' market shares as in Atkeson and Burstein (2008).

The left panel of Figure 1 shows the evolution of the cumulative consumer price index (CPI) in the U.S. starting from the business cycle trough for each of the past five economic expansions. As the figure shows, each recovery is associated with a lower cumulative consumer price inflation compared to the previous one, with cumulative CPI increasing by 25% in the first 20 quarters of the recovery following the 1981-82 recession, by 15% following the 1990-91 recession, and by less than 10% over 20 quarters in the last expansion.

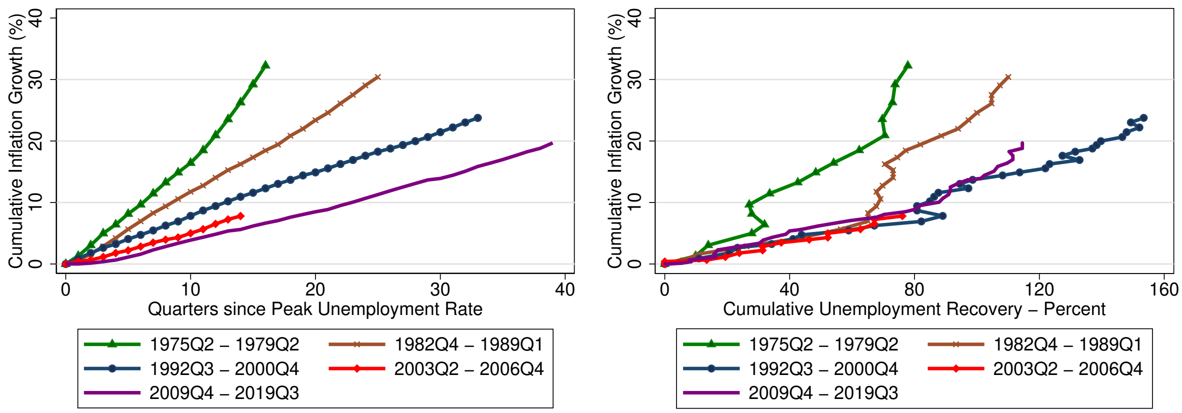
While the evolution of consumer price inflation over time is informative, the duration of expansions is an increasingly misleading indicator of labor market recovery given the emergence of jobless recoveries. We therefore propose a novel but simple measure of labor market recovery that is consistent across expansions—*the unemployment recovery gap*—and consider the evolution of price inflation with respect to this new measure. Our new metric computes the share of the rise in the unemployment rate during the preceding recession that has been reversed during the current expansion. An unemployment recovery gap of 100% thus implies that the unemployment rate has declined back to its pre-recession trough.[2] In the right panel of Figure 1, we plot the evolution of cumulative CPI inflation relative to this new metric. The 1970s and the early 1980s clearly stand out as expansionary periods

[1] NY Times Upshot: Janet Yellen and the Case of the Missing Inflation, June 14, 2017; Living Life Near the ZLB, John C. Williams, Remarks at 2019 Annual Meeting of the Central Bank Research Association (CEBRA), New York City, July 18, 2019.

[2] There are alternative measures of labor market utilization that capture wage-growth better than the unemployment rate such as the NEI developed by Hornstein et al. (2014), the tightness measure developed in Moscarini and Postel-Vinay (2017a) and the aggregate hours gap in Faberman et al. (2020). These alternative measures of labor market utilization typically start in 1994 due to CPS redesign. We focus on the unemployment recovery gap measure due to its simplicity and availability of a longer time series.

Figure 1: Evolution of Core CPI Inflation During Economic Expansions

(a) Inflation over Time (b) Inflation versus Unemployment Recovery



Source: BLS and authors' calculations. Note: The left panel plots the cumulative core CPI inflation (All items less food and energy, seasonally adjusted) against time, starting at the quarter of peak unemployment of a given recession. The right panel plots the same data against the unemployment recovery gap defined in the main text.

with inflation picking up rapidly after the end of the recessions. The three most recent expansions exhibit a milder rise in cumulative inflation. Thus, even taking into account the emergence of jobless recoveries, the behavior of inflation changed considerably after 1990. This observation is consistent with the decline in the slope of the price Phillips curve as documented in detail in Stock and Watson (2019) and the references therein.

We examine inflation in goods and in services and identify a notable change in the behavior of core goods inflation. While core goods prices rose by about 20% as unemployment fell from recessionary peak to trough during the 1982-89 expansion, core goods prices barely increased in the 2009-2020 expansion. At the same time, core services inflation has picked up in all expansions. We analyze a counterfactual scenario in which goods prices behave in the 2009-2020 expansion in the same way as they did during the 1982-89 expansion. We show that around 50% of the missing inflation relative to the 1980s expansion can be traced to goods prices despite core goods having a weight of only 25% in the CPI. Interestingly, our empirical analysis shows that the change in inflation dynamics is not driven by a differential behavior of wages. Wage inflation has been similar in goods and in services in the last two expansions. This result is consistent with Galí and Gambetti (2019) and Stock and Watson (2019) who find a more stable Phillips curve for wages.

These findings suggest that the changing pass-through from wage changes to price changes is a promising explanation for the missing core goods inflation. To investigate this possibility, we estimate the impulse responses to changes in wage inflation on both consumer and producer price inflation following Jordà (2005). We uncover a striking change in the relative behavior of wage and price inflation: pass-through from wages to prices was significant and positive until the early 2000s, but then dropped sharply and has been statistically indistinguishable from zero in the last two decades. The Wald test for a structural break identifies a structural break in 2004/Q3 for the CPI and in 2002/Q4 for the PPI.

Our paper proposes two related explanations for the disappearance of wage-price pass-through: rising import competition and increasing market concentration. A substantial literature has documented an increase in import competition in the U.S. manufacturing sector since China's WTO entry in the early 2000s (e.g., Autor et al. (2013)). At the same time, recent work has pointed out that market concentration in manufacturing has increased (e.g., Autor et al. (2020)). We theoretically examine how these two channels affect pass-through by setting up a model with imperfect competition à la Atkeson and Burstein (2008). In the model, there is a continuum of industries populated by firms that have market power. Each industry contains both foreign and domestic firms, where the former are assumed to face a different wage process than the latter. Firms set prices taking into account their strategic interaction with other firms, and internalize the effects of changing their price on their market share. We derive a pass-through equation that links price changes to firms' productivity, input prices, and the endogenous markup, and show that the pass-through of wage shocks into prices depends on a firm's labor share and the structure of a firm's industry.

The model generates two main implications: first, when foreign firms account for a larger share of the market, fewer firms experience a domestic wage shock. As a result, fewer firms are compelled to adjust their price, causing domestic firms to absorb more of the wage shock into their markup in order to preserve market share against their foreign competitors. Therefore, the model predicts that rising import penetration reduces pass-through from domestic wages into prices. Second, domestic firms with a higher market share are more sensitive to the strategic interaction with their competitors. In response to a wage shock, they change their price by less in order to remain competitive against the unaffected foreign firms. Since the average firm in a more concentrated industry tends to have a higher market share, more concentrated industries have lower wage-price pass-through.

We examine these implications using detailed industry-level data from the Bureau of Labor Statistics (BLS) and the U.S. Census Bureau. Our analysis focuses on producer price inflation to link wages and prices at the industry-level, and uses the manufacturing sector as a proxy for the goods-producing sector. We implement the theoretically derived pass-through regression empirically and estimate impulse responses for the manufacturing and services industries separately in our disaggregated data. To account for the fact that pass-through of wage changes depends on an industry's share of labor in total production, we estimate the regressions controlling for each industry's labor share. We find that pass-through is significant in services industries but insignificant or negative in manufacturing. Over an eight-quarter horizon, pass-through from wages to producer prices in manufacturing is essentially zero, while we estimate a pass-through of 52% per unit of labor in services. This result implies that a 10% increase in labor costs is associated with a 5.2% increase in service prices in an industry with a labor share of one. We also estimate cumulative pass-through using an instrumental variables local projection (IV-LP) following Ramey (2016) which allows us to take into account the dynamic effects of a shock on wages themselves. We find that even when we take into account dynamic effects, there is no pass-through from wages to prices in manufacturing over a horizon of twenty quarters. In contrast, we find significant and positive pass-through in services.

We then turn to our two hypotheses and show that higher import penetration and higher market concentration are correlated with lower pass-through. We exploit the availability of a longer time series in manufacturing to document that the pass-through from wages to prices in that sector has declined over the last two decades, consistent with the rise in trade and concentration during that period. While pass-through over an eight-quarter period was 50% per unit of labor until the early 2000s, it has been essentially zero since then. We then document that industries that are exposed to more import competition exhibit lower wage to price pass-through. While an industry with no change in import penetration since 1997 exhibits a pass-through from wages to prices of about 40% per unit of labor, pass-through would be reduced to 20% in an industry with the average increase in import penetration since 1997 of 17 percentage points. Consistent with our second hypothesis, we also find that high market concentration is linked to lower pass-through. While a doubling of wages translates into an 88% price increase per unit of labor in a perfectly competitive industry, it would only correspond to a 17% price increase per unit of labor in an industry with the average top-4 concentration of 36%. We incorporate both mechanisms into the same pass-through regression and find that once we control for import penetration and concentration, pass-through in manufacturing remains positive in the post-2003 period. We also show that import penetration and market concentration are positively correlated across industries, consistent with Amiti and Heise (2021), who show that rising import competition caused an increase in domestic concentration over the last three decades.

To summarize, our theory and empirical findings suggest a simple mechanism for the declining pass-through in manufacturing. The entry of foreign competitors into the U.S. market caused many domestic firms to exit, contributing to the increasing U.S. domestic market concentration (as argued by Gutiérrez and Philippon (2017) and Amiti and Heise (2021)). Consequently, the surviving, relatively large U.S. firms were able to charge on average higher markups, which made it possible for them to at least partially absorb cost-push shocks without passing them to their consumers. These firms take into account that by raising their prices they lose market share to foreign competitors that may not have experienced the same shock. In contrast, firms which operate in more competitive markets have low markups and are therefore forced to pass through shocks more fully.

Our paper is closely related to the recent literature examining the puzzling inflation dynamics during and after the Great recession. Coibion and Gorodnichenko (2015), Del Negro et al. (2015), Carvalho et al. (2017), Crump et al. (2019), and Coibion et al. (2019) all emphasize the role of inflation expectations in accounting for the behavior of inflation, while Bugamelli et al. (2015), Forbes (2019), and Obstfeld (2020) point to the global aspects of inflation. Peach et al. (2013) point out the different dynamics of core goods and core services inflation more broadly. Our analysis complements these papers by explicitly focusing on the disappearing pass-through from wages to prices in the goods sector and by linking it to important changes in the U.S. economy in the last two decades.

Our analysis is also consistent with the recent literature on the changing nature of the wage and price Phillips curves. We find that despite the decoupling of unemployment and prices in the goods sector in the recent decades, there is no disconnect between unemployment and wages once changing unemployment dynamics are taken into account—a finding that echoes Stock and Watson (2019).

The rest of the paper is organized as follows. Section 2 defines our measure of labor market recovery and establishes the aggregate facts regarding behavior of inflation, wages and productivity during expansions. Section 3 introduces our theory and develops a pass-through equation which we then implement empirically to analyze the pass-through of wages to prices in manufacturing and services. Section 4 investigates the effect of rising import competition and increasing market concentration. Finally, Section 5 concludes.

2 Changing Inflation Dynamics and Goods Inflation

We begin our analysis by showing that the changing behavior of goods prices is an important driver of the slower pick-up of consumer price inflation during recent expansions. The behavior of prices for services is in line with earlier expansions.

Our comparison of inflation across different recessions needs to take into account the changing output and unemployment dynamics over time (see, for example, Galí et al., 2012; Jaimovich and Siu, 2020). One possibility is that inflation may have been slow to pick up in more recent recessions simply because the labor market has become slower to recover. That is why studying the evolution of inflation over time could be misleading.

To have a consistent metric of labor market recovery over time, we propose a simple measure of labor market recovery—*the unemployment recovery gap*—and consider the evolution of price inflation with respect to this new measure. We consider the share of the rise in the unemployment rate during the preceding recession that has been reversed during the following expansion. Specifically, for each recession, we identify the peak quarterly unemployment rate, u_{peak} and compute the increase in the unemployment rate relative to its preceding trough, u_{trough}. This allows us to evaluate the progress in the unemployment rate $u_{peak} - u_t$ as a fraction of the unemployment gap $u_{peak} - u_{trough}$. We refer to this metric as the *unemployment recovery gap* and define it as

$$URecovery_t = \frac{u_{peak} - u_t}{u_{peak} - u_{trough}}. \quad (1)$$

For example, a value of 100% indicates that the unemployment rate is back to its pre-recession trough. As is well documented, $URecovery_t$ takes longer to achieve 100% in more recent expansions, consistent with the emergence of jobless recoveries. Our new measure captures the fact that employment-output dynamics have changed over time and is simple and easy to track.

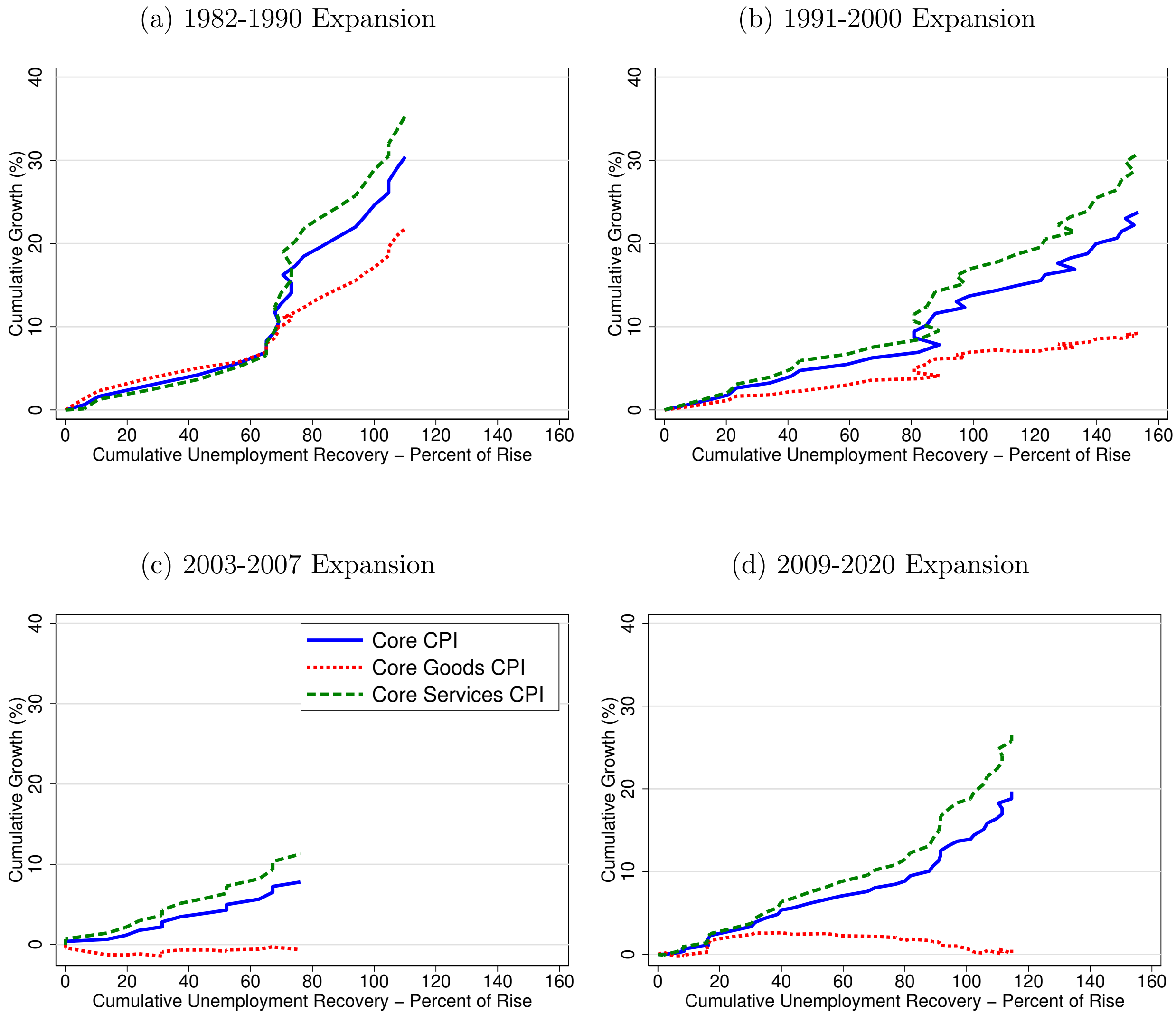
We begin our analysis by studying the relationship between *cumulative* price growth with the unemployment recovery gap in the last four expansions. Figure 2 shows the cumulative growth in consumer prices (CPI-U core inflation) for core goods and for core services relative to the unemployment recovery gap starting from the peak unemployment rate in each episode.[3]

This figure establishes our first fact: Growth in core goods prices has slowed notably over time. While core goods prices rose by about 20% as unemployment fell from peak to trough following the 1981-82 recession (Figure 2a), after the 2001-02 and 2007-09 recessions core goods prices barely picked up (Figures 2c and 2d). At the same time, the recovery of core services inflation has been roughly similar across expansions. We show that these results are robust to alternative definitions of economic activity and employment in Appendix A.

To isolate the role of declining goods inflation in accounting for low CPI inflation, we compute the counterfactual cumulative inflation that would have prevailed had goods prices behaved in the same was as they did following the 1981-82 recession. Specifically, we compute the path of counterfactual inflation for the 2003-2007 and 2009-2020 expansions using the core goods CPI in the expansion following the 1981-82 recession. We keep the core CPI in services and the weights of two sectors at their current levels. Figure 3 shows that around

[3]Our motivating facts are based on aggregate price data from the Bureau of Labor Statistics (BLS). We obtain the quarterly, seasonally adjusted Consumer Price Index (CPI-U) for commodities excluding food and energy (core goods) and for services excluding energy services (core services). Our measure of unemployment is the quarterly, seasonally adjusted unemployment rate of workers 16 years and older from the BLS.

Figure 2: Inflation versus Unemployment Recovery from Four Previous Recessions

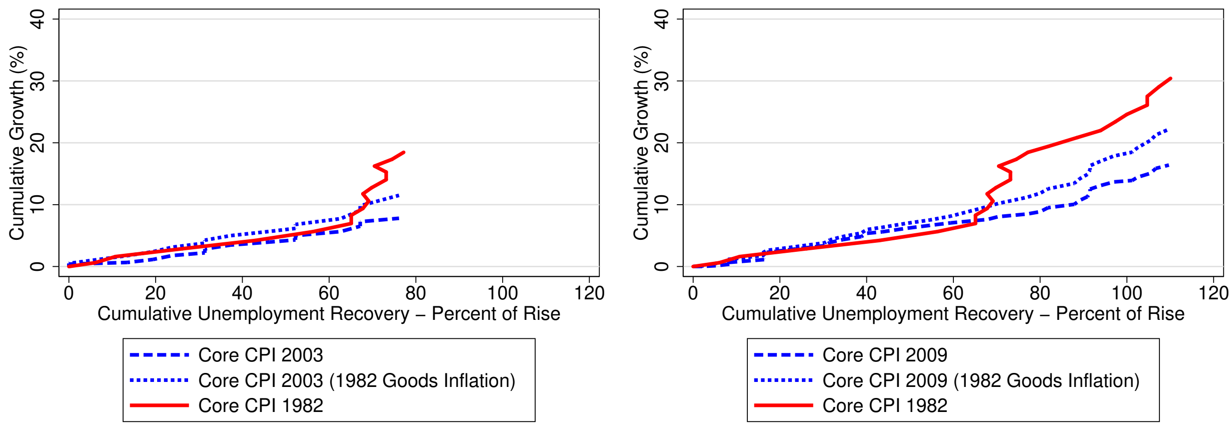


Source: BLS and authors' calculations. Note: The blue line in each panel plots the cumulative core CPI inflation (all items less food and energy, seasonally adjusted) against the unemployment recovery gap measure defined in the text, starting at peak unemployment of a given recession. The red dotted line shows the core goods CPI (commodities less food and energy commodities, seasonally adjusted) and the green dashed line presents core services CPI (services less energy services, seasonally adjusted).

50% of the weakening of inflation in the 2003-2007 and 2009-2020 expansions relative to the 1980s expansion can be traced to goods prices. Even though core goods inflation has a weight of only about 25% in the overall CPI in the 2000s, the change in its behavior accounts for half of the missing inflation. This finding implies that the behavior of core goods inflation is important in understanding the changing behavior of inflation.

Figure 3: Counterfactual Inflation for the 2003-2007 and 2009-2020 Expansions

(a) 2003-2007 Expansion (b) 2009-2020 Expansion



Source: BLS and authors' calculations. Note: Each panel shows cumulative core CPI inflation (seasonally adjusted) since peak unemployment against the unemployment recovery gap measure defined in the text. The dashed blue line presents the actual cumulative core CPI inflation in a given recovery. The dotted blue line shows a counterfactual where cumulative goods inflation for a given unemployment recovery gap is replaced with its analogue in the expansion following the 1982 expansion. The red solid line shows the cumulative core CPI inflation in 1982 for comparison.

Role of Labor Costs

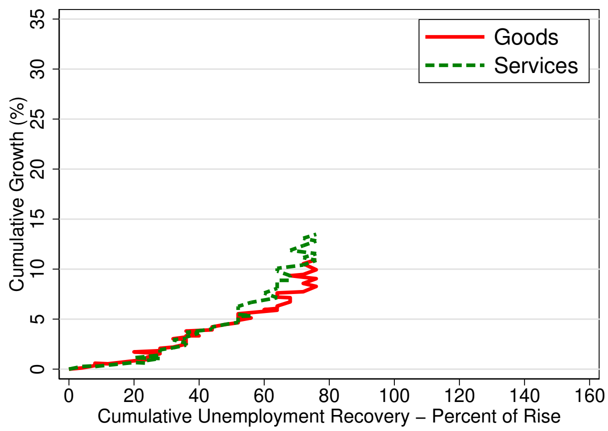
One possible explanation for the changed behavior of goods inflation could be a different behavior of labor costs in goods and in services. Slower inflation pickup for goods prices might simply be a reflection of slower wage growth in goods-producing industries than in services. To examine this possibility, we consider two measures of labor cost growth for the two most recent expansions in Figure 4: hourly earnings of production workers (top panels), and unit labor costs (bottom panels).[4] The top panels of the figure show that wage dynamics were similar in both goods and services sectors. In particular, the data do not show a slowdown in wage growth in the goods-producing sector.

While hourly earnings are informative, they do not control for potential differences in productivity growth in goods and services sectors. The bottom panels therefore show overall unit labor costs for the U.S. economy along with the unit labor costs in manufacturing. The figures show that unit labor cost in manufacturing did not grow in the 2003-2007 expansion despite declining unemployment. However, the 2009-2020 expansion looks different with the unit labor cost in manufacturing picking up faster than overall labor costs after the unemployment gap closed. Therefore, we conclude that goods inflation did not pick up

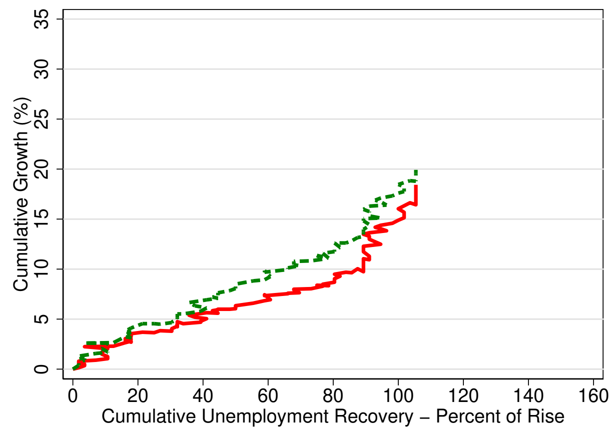
[4]We use average hourly earnings of production and non-supervisory workers, seasonally adjusted, and unit labor costs from the BLS.

Figure 4: Cumulative Growth in Wages (Top Panels) and in Unit Labor Costs (Bottom Panels) Relative to Unemployment Recovery Gap

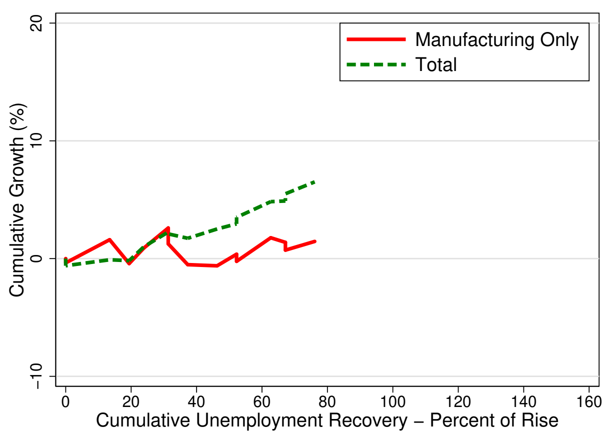
(a) Wage Growth: 2003-2007 Expansion



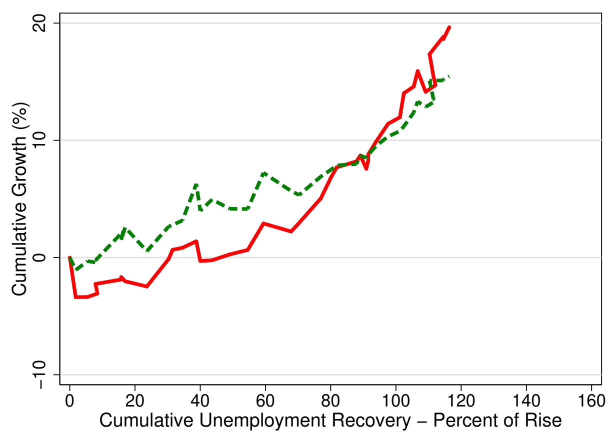
(b) Wage Growth: 2009-2020 Expansion



(c) Unit Labor Cost: 2003-2007 Expansion



(d) Unit Labor Cost: 2009-2020 Expansion



Source: BLS and authors' calculations. Note: The top two panels plot the cumulative wage inflation in two economic recoveries against the unemployment recovery gap defined in the main text, starting at peak unemployment of the previous recession. Wages are defined as average hourly earnings of production and non-supervisory employees, seasonally adjusted, in the goods-producing industries and service-providing industries, respectively. The bottom two panels present similar figures for unit labor costs, for the manufacturing sector and for the overall U.S. economy.

despite improving labor market conditions and rising labor costs in the 2009-2020 expansion. These findings imply that lack of pass-through from labor costs to prices in the goods sector is likely an important channel which we directly examine next.

Role of Pass-through from Wages to Prices

We analyze pass-through from wages to prices directly using aggregate data and the local projection method following Jordà (2005). In particular, we estimate the impulse response of price inflation to changes in wage inflation for each quarter $h = 0, ..., 20$

$$\pi_{t+h}^{\text{price}} = \alpha + \beta_h \pi_t^{\text{wage}} + \sum_{j=1}^{8} \delta_j \pi_{t-j}^{\text{price}} + \sum_{j=1}^{8} \zeta_j \pi_{t-j}^{\text{wage}} + \sum_{j=1}^{8} \eta_j z_{t-j} + \epsilon_t, \quad (2)$$

where π_{t+h}^{price} is the inflation rate of prices in quarter $t+h$ and π_t^{wage} is wage inflation in quarter t. We also include eight lags of the wage inflation rate π_{t-j}^{wage}, the price inflation rate π_{t-j}^{price}, and the unemployment gap z_{t-j}. The latter variable is obtained from the Congressional Budget O□ce (CBO), and captures that price inflation will be lower when the unemployment gap is higher.

We use two measures for price inflation: the core CPI as above and a *core* Producer Price Index (PPI) capturing the inflation of finished goods less food and energy. The producer price index captures the prices charged by producers of goods, both to consumers and to other firms. We measure wage inflation as average hourly earnings of production and supervisory workers. Both price inflation and wage inflation measures have been annualized to facilitate the interpretation of the results. Our sample starts in 1964 for the CPI and in 1974 for the PPI. As shown in Jordà (2005), the regression can be approximately interpreted as a VAR under a Cholesky decomposition.

Figures 5a and 5b present the impulse response of core CPI and core PPI, respectively, to an innovation in average hourly earnings. We find a strong positive pass-through from wage growth to inflation. CPI inflation rises for about 12 quarters and peaks around 1, while PPI inflation peaks after 8 quarters at a slightly higher level. To investigate the stability of this pass-through over time, we next estimate equation (2) over 25-year rolling windows and plot the resulting pass-through at the peak lag length ($h = 12$ for the CPI and $h = 8$ for the PPI) in Figures 5c and 5d over time. These results show that the pass-through has significantly declined over time. Pass-through was significant and positive until the early 2000s, then dropped sharply and is currently statistically indistinguishable from zero.[5]

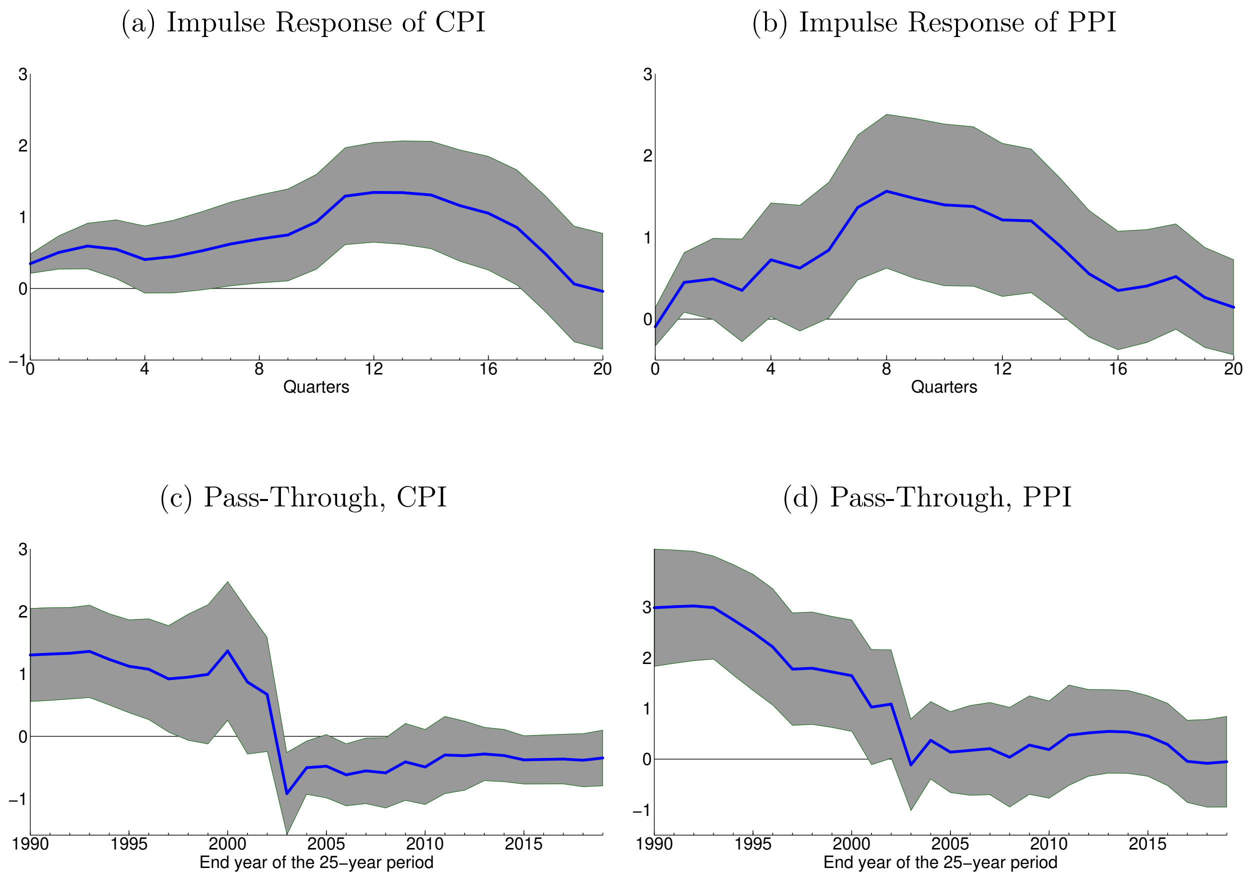
To examine the timing of potential breaks in the data, we perform a Wald test for a structural break based on specification (2) at the lag length with the peak pass-through for both series.[6] Table 1 reports the results. We find a significant structural break in 1980/Q2 for the CPI and in 1982/Q3 for the PPI. This structural break is not surprising since it marks the beginning of the Volcker disinflation period. We perform another structural break test for the post-1993 period using the same specification and identify another structural break in 2004/Q3 for the CPI and in 2002/Q4 for the PPI.

While our aggregate pass-through estimates show a stark decline in pass-through, they

[5]In Appendix A we show that this result is robust to alternative specifications of equation (2).

[6]We include only 4 lags of all variables to have enough of a time series for the PPI

Figure 5: Aggregate Pass-Through of Price Inflation to Wage Inflation



Source: BLS and authors' calculations. Note: The top two panels present the estimated coefficients β_h and their 90 percent confidence intervals from specification (2) run at quarterly frequency, for horizons $h = 0, ..., 20$ quarters. In the top left panel, price inflation is core CPI inflation (All items less food and energy, seasonally adjusted) and wage inflation is average hourly earnings of production and non-supervisory employees. The unemployment gap z_t is the unemployment rate minus the natural rate of unemployment (NAIRU) from the CBO. All variables are transformed into a quarterly series by taking a simple average across the months in each quarter. In the top right panel, price inflation is the producer price index (PPI) of finished goods less food and energy. The bottom two panels estimate specification (2) over 25-year rolling windows for $h = 12$ for the CPI and $h = 8$ for the PPI, where the ending year of the 25-year period is indicated on the x-axis.

have two main shortcomings. First, we cannot identify the sectors that are driving the decline in pass-through. Second, time-variation is limited in scope and lack of shocks or instruments leads to a potential simultaneity bias. To address these issues, in the remainder of empirical analysis we rely on rich industry-level variation using detailed data on wages and prices.

3 Pass-Through from Wages to Prices

Our analysis so far suggests that a decline in the pass-through of labor costs to prices could be behind the weaker inflation observed in the last two decades. In this section, we first

Table 1: Structural Breaks

Series	Time Period	Structural Break	Wald Test Statistic
CPI	1964-2020	1980	672.71***
CPI	1993-2020	2004	169.46***
PPI	1974-2020	1982	246.09***
PPI	1993-2020	2002	154.29***

Note: The table presents statistics for a structural break Wald test based on specification (2), run at quarterly frequency, where we use only 4 rather than 8 quarter lags of each variable. Price inflation is core CPI inflation (All items less food and energy, seasonally adjusted) in rows 1-2 and the producer price index (PPI) of finished goods less food and energy in rows 3-4. Wage inflation is average hourly earnings of production and non-supervisory employees. The unemployment gap z_t is the unemployment rate minus the natural rate of unemployment (NAIRU) from the CBO. Column 1 shows whether we use CPI or PPI inflation. Column 2 indicates the time period considered for the test. Column 3 shows the year of the structural break. Column 4 presents the Wald test statistic. *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively.

introduce a theoretical framework in which pass-through is based on fundamentals such as the market structure, the labor share, and productivity. We then implement our empirical analysis using industry-level data and interpret our findings in light of our theoretical framework. We find that pass-through from wages to prices in goods-producing industries has been negligible in the last two decades, while it remains significant and positive in services.

3.1 A Framework Linking Pass-Through and Competition

Our theoretical framework builds on the model developed in Atkeson and Burstein (2008). The framework allows us to derive estimating equations to examine the importance of rising concentration and increasing import competition on wage to price pass-through. We examine the pass-through of a domestic cost shock to prices, and study explicitly how this pass-through varies with concentration and the share of foreign firms. We conduct our analysis in partial equilibrium since our focus is the comparative statics of pass-through while Atkeson and Burstein (2008) focus on movements in international relative prices.

3.1.1 Model Environment

The model consists of several agents. At the lowest level of aggregation are individual firms, which produce varieties. The varieties are aggregated into industries. These industries are aggregated into two sectors, goods and services. We next analyze how prices in one of these sectors are determined.[7]

A competitive firm produces output using inputs from a continuum of industries $k \in [0, 1]$, which are aggregated according to the CES production function

[7] We omit a sector subscript to simplify notation. To focus on pass-through and to facilitate the model's exposition, we do not explicitly model a household sector.

$$Y = \left(\int_0^1 y(k)^{(\sigma-1)/\sigma} dk \right)^{\sigma/(\sigma-1)}, \tag{3}$$

where $y(k)$ denotes the output produced by industry k and σ is the elasticity of substitution between industries. Standard arguments imply that the demand curve for goods of industry k is obtained as

$$y(k) = \left(\frac{p(k)}{P} \right)^{-\sigma} Y, \tag{4}$$

where $P = (\int_0^1 p(k)^{1-\sigma} dk)^{1/(1-\sigma)}$ and $p(k)$ is the industry's price index.

Each industry is populated by a finite number of firms, $N(k)$. These firms can either be foreign (f) or domestic (d), with $F(k)$ the number of foreign firms in industry k and $D(k)$ the number of domestic firms. The industry-specific aggregator of varieties is given by

$$y(k) = \left(\sum_{f=1}^{F(k)} y(k,f)^{(\eta-1)/\eta} + \sum_{d=1}^{D(k)} y(k,d)^{(\eta-1)/\eta} \right)^{\eta/(\eta-1)}, \tag{5}$$

where η is the elasticity of substitution across varieties, and $y(k,i)$, with $i \in \{F, D\}$, is the quantity of firm i's variety in industry k. The demand for variety (k,i) is given by

$$y(k,i) = p(k,i)^{-\eta} p(k)^{\eta-\sigma} P^{-\sigma} Y, \tag{6}$$

where $p(k) = (\sum_{i=1}^{N(k)} p(k,i)^{1-\eta})^{1/(1-\eta)}$.

Each firm has a constant returns to scale production function that combines labor and capital according to

$$y = A l^{\alpha} k^{1-\alpha} \tag{7}$$

where A is total factor productivity, l is labor, and k is capital. We assume that all firms face the same capital costs, but face a local wage rate $w(i)$. Specifically, we assume that $w(i) = w_D$ for all domestic firms, and $w(i) = w_F$ for foreign firms. Standard cost minimization formulates the marginal cost of the firm to produce $y(k,i)$ amount of output as a function of wage, $w(i)$, and the rental rate of capital, r, as

$$c(k,i) = \frac{1}{A} w(i)^{\alpha} r^{1-\alpha}. \tag{8}$$

Factor prices are determined competitively and taken as given by each firm.[8]

As in Atkeson and Burstein (2008), we assume that varieties are more substitutible across

[8] We have omitted the constant for simplicity and all details are delegated to Appendix B.

firms in the same industry than across industries, $\eta > \sigma > 1$. Firms compete under Bertrand competition, taking as given the prices chosen by other firms when setting their price, and taking as given input costs. Since there is only a finite number of firms, each firm takes into account the effect of its price setting on the price index $p(k)$. Firms therefore face an effective elasticity of demand of

$$\mathcal{E}(k,i) = \eta(1-\varphi(k,i)) + \sigma\varphi(k,i), \tag{9}$$

where $\varphi(k,i) = (p(k,i)y(k,i))/(\sum_{i'} p(k,i')y(k,i'))$ is firm i's market share in industry k. Intuitively, firms with a higher market share are less concerned with competition from firms within their industry, and are focused more on competition across industries, which lowers their effective demand elasticity.

3.1.2 Pass-Through of Shocks to Prices

Each firm solves

$$\max_p \left[p - c(k,i)\right] \left(\frac{p}{p(k)}\right)^{-\eta} \left(\frac{p(k)}{P}\right)^{-\sigma} Y. \tag{10}$$

The solution of this problem, taking into account that firms take into consideration the impact of their own price setting on the industry's price index, is

$$p(k,i) = \frac{\mathcal{E}(k,i)}{\mathcal{E}(k,i)-1} c(k,i), \tag{11}$$

where $\mathcal{M}(k,i) \equiv \mathcal{E}(k,i)/(\mathcal{E}(k,i)-1)$ is the firm's markup. Firms with a larger market share set higher markups since they face less elastic demand.

In Appendix B.1, we show that we can derive the pass-through of shocks into prices as

$$d\log p(k,i) = d\log \mathcal{M}(k,i) - d\log A + \alpha d\log w(i) + (1-\alpha) d\log r. \tag{12}$$

Thus, pass-through of wage shocks is equal to α plus a term that captures the adjustment of the markup. This specification will be our key estimating equation below.

Our model structure allows us to express the change in the markup as a function of other variables related to market structure. Using the definition of the markup and the effective demand elasticity, we find that the change in the markup can be written as

$$d\log \mathcal{M}(k,i) = -\Gamma(k,i) \left[d\log p(k,i) - d\log p(k)\right], \tag{13}$$

where $\Gamma(k,i) = -(\partial \log \mathcal{M}(k,i)/\partial \log p(k,i)) \geq 0$ is the elasticity of the markup with respect to a firm's own price. We therefore have from equations (12) and (13) that a firm's pass-through is given by

$$d \log p(k,i) = -\Gamma(k,i)\left[d \log p(k,i) - d \log p(k)\right] - d \log A + \alpha d \log w(i), \tag{14}$$

where we have omitted r since it is constant. Solving this equation for $d \log p(k,i)$, we find

$$d \log p(k,i) = \frac{\Gamma(k,i)}{1+\Gamma(k,i)} d \log p(k) - \frac{1}{1+\Gamma(k,i)} d \log A + \frac{\alpha}{1+\Gamma(k,i)} d \log w(i). \tag{15}$$

This equation highlights the key mechanisms that affect pass-through of wage shocks: first, there is a direct effect coming from the change in $w(i)$. Second, there is an indirect effect that operates via the change in the industry's price index, $p(k)$. The relative strength of the two channels is modulated by the markup elasticity $\Gamma(k,i)$. Firms with a higher markup elasticity put a higher weight on the aggregate price index. The equation also illustrates that increases in productivity tend to reduce prices.

The markup elasticity is increasing in a firm's market share, holding everything else fixed, $d\Gamma(k,i)/d\varphi(k,i) > 0$, and satisfies $\Gamma(k,i) = 0$ if $\varphi(k,i) = 0$ (see Appendix B.1.4). It follows from equation (15) that when adjusting their price in response to a shock, firms with a higher market share put greater emphasis on the movement of the industry's overall price index than firms with a lower market share.

We can now discuss the two main implications of the theory. First, a higher share of foreign firms in an industry implies that fewer firms experience a given domestic wage shock. From equation (15), firms place some weight on the industry's overall price index, $p(k)$, when adjusting their price. Since the direct effect on this index is smaller when fewer firms are affected by the wage shock, domestic firms change their price $p(k,i)$ by less in response to the shock when foreign firms are more important in an industry. Consequently, pass-through falls. Intuitively, domestic firms absorb more of the shock into their markup in order to preserve market share against their foreign competitors which were unaffected by the shock.

Second, since $\Gamma(k,i)$ is increasing in firms' market share, firms with a higher market share are more sensitive to the strategic interaction with their competitors, placing more emphasis on the industry's price index $p(k)$ relative to the direct effect of a wage shock. When some firms in the industry are foreign, the industry's price index moves by less than the direct wage effect. As a result, pass-through is less than complete. As concentration in an industry rises, the market share of the average firm tends to go up, increasing the emphasis on the industry's price index, and pass-through falls.

We summarize these insights in the following proposition.

Theorem 3.1. *Consider an industry populated by a finite number of $D(k) \geq 1$ domestic firms and $F(k) \geq 1$ foreign firms. Market shares are symmetric for all firms, with the market shares of the $D(k)$ domestic firms summing up to $\varphi_D(k)$ and the market shares of the $F(k)$ foreign firms summing up to $\varphi_F(k)$. Consider a domestic wage shock, $dw_D > 0$.*

1. *Pass-through of the shock by domestic firms decreases in their concentration: for a given $\varphi_D(k)$, pass-through is lower when $D(k)$ is smaller.*

2. *Pass-through of the shock by domestic firms decreases in the overall market share of foreign firms: holding fixed each individual firm's market share $\varphi(k,i)$, substituting a foreign firm for a domestic firm reduces pass-through.*

Proof. See Appendix B.2. □

Our empirical analysis is built on these insights and relies on industry-level data to examine the change in pass-through over time.

3.2 Estimating Pass-through From Wages to Prices

We analyze changes in prices in response to wage growth across industries using disaggregated industry-level data on producer prices, wages, and productivity. We estimate pass-through regressions at different time horizons and examine the impact of wages on and the role of the labor share.[9]

3.2.1 Pass-through Estimates

We implement a version of our estimating equation (12) derived in the theory in the data. To show that our conclusions are not dependent on one specific horizon, we estimate the regression over different time horizons. Specifically, we estimate

$$\Delta_{t-h,t} \ln(p_{it}) = \beta_h \Delta_{t-h,t} \ln(w_{it}) + \gamma X_{it} + \delta_i + \rho_t + \epsilon_{it}, \tag{16}$$

where $\Delta_{t-h,t} \ln(p_{it})$ is the log producer price change between quarter $t-h$ and quarter t in industry i, and $\Delta_{t-h,t} \ln(w_{it})$ is the corresponding wage change over the same time horizon. The controls X_{it} include the change in industry i's TFP over time horizon h, as well as controls for the composition of the industry's workforce in quarter t. Specifically, we include the shares of prime-aged and older workers, the share of female workers, and the

[9] As an alternative, in Appendix C, we implement the same local projection framework that we used in the aggregate data and show that the conclusions are similar, although the coefficients are less precisely estimated.

shares of workers with a high-school degree, associates degree, and bachelors degree or higher. While we do not observe industry-specific capital costs, we control for fixed differences across industries by including industry fixed effects δ_i, and we control for macroeconomic trends by adding time fixed effects ρ_t. These time fixed effects also pick up variation in the aggregate unemployment gap, which is therefore not included separately. We weight the regression by an industry's total sales in 2012, and use Driscoll-Kraay standard errors with bandwidth two quarters to account for cross-sectional and time series correlation. The coefficient β_h captures the pass-through of wage changes to price changes over a horizon of h quarters. If markups are constant and capital costs are uncorrelated with wage changes, then according to the simple framework above β_h is the labor share α. The coefficient is identified by comparing how much of a higher wage growth in one sector relative to the others translates into a higher growth in producer prices in that sector.

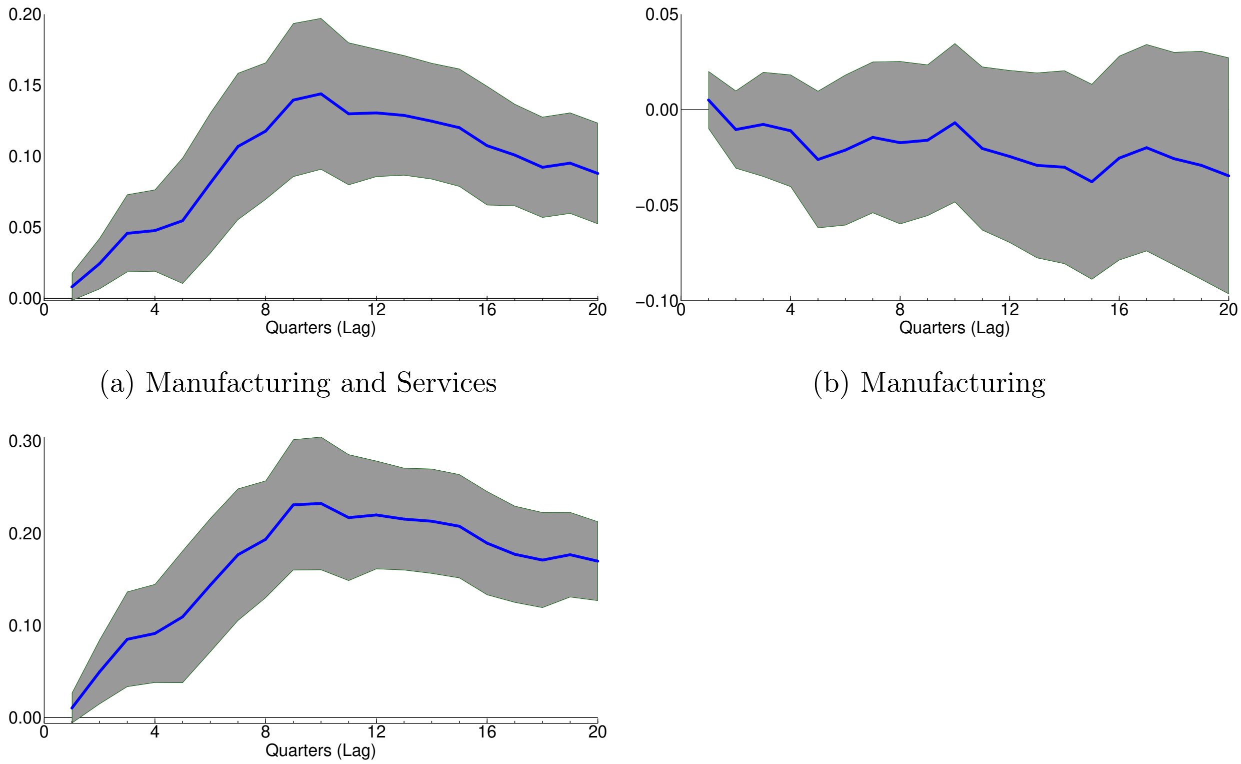
Our empirical implementation combines several publicly available data sources. For price data, we use the seasonally-adjusted, industry-level Producer Price Index (PPI) series from the BLS. We analyze producer prices because producer prices are available at the industry-level, allowing for a clean mapping between industry-level wages and prices unlike the CPI. Moreover, as we have shown, the decline in pass-through over time in the aggregate data was similar in consumer and producer prices. To compare goods and services, we focus on the manufacturing sector as a proxy for goods-producing industries since we have a long and consistent time series for this sector.[10] For wages, we obtain average weekly earnings from the Quarterly Census of Employment and Wages (QCEW) from the BLS, and seasonally adjust them using the Census Bureau's X-12 ARIMA program. In principle, hourly earnings would be preferable to account for changes in hours worked. In practice, however, using the QCEW has several advantages over other datasets. First, the QCEW provides comprehensive coverage of all establishments in the United States, covering about 10.4 million establishments and including nearly all workers covered by social security. Second, the QCEW wages reflect *total compensation*, including bonuses, stock options, and tips, as well as 401(k) plans for some states.[11] Third, the QCEW provides comprehensive wage data for nearly all 5-digit NAICS industries. These advantages make the data preferable to a less comprehensive and less accurate dataset such as the Current Employment Statistics (CES).

Our baseline pass-through dataset combines quarterly price and wage data at the 5-digit NAICS level. We generate time-consistent NAICS industries by concording the NAICS codes using the correspondences provided by the U.S. Census Bureau. In total, we have

[10] Manufacturing accounted for about 63% of employment in goods-producing industries in the last decade.

[11] While the Employment Cost Index (ECI) also has information about non-wage labor costs, it is not available at the level of disaggregation we require for our industry-level analysis.

Figure 6: Pass-Through at Different Time Horizons



(a) Manufacturing and Services

(b) Manufacturing

(c) Services

Source: BLS, Census Bureau Quarterly Census of Employment and Wages, authors' calculations. Note: The figure presents the estimated coefficients β_h from specification (16) and their 90 percent confidence intervals for changes computed over $1, ..., 20$ quarters. Prices are the seasonally-adjusted producer price indices and wages are the seasonally-adjusted average weekly wages of 5-digit NAICS industries. All data are at the quarterly frequency. Controls in the regression are TFP, employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Panel (a) presents the estimated coefficients β_h based on a regression using all industries in our sample. Panels (b) and (c) are constructed by running specification (16) where we replace the wage change with two interaction terms, one that interacts the wage change with a dummy for whether an industry is in manufacturing and the other that interacts the wage change with a dummy for whether the industry is in services. We plot the coefficients on these two interactions.

information for 255 industries at the 5-digit level, of which 148 are in manufacturing. The first available year where we have price information for both manufacturing and services is 2003.[12] Appendix D provides more details.

We first run regression (16) for h ranging from 1 to 20 quarters. The top left panel of Figure 6 shows the estimated coefficients β_h as well as 90 percent confidence intervals. The figure shows that pass-through from wages to prices is positive and significant at all horizons, reaching a peak at $h = 10$ quarters. We next estimate the same regression specification but interact the change in wages with two dummies capturing whether the industry is in the manufacturing or services sector. The two coefficients on these interactions, $\beta_{h,manuf}$ and

[12] We exclude petroleum and coal products (NAICS 324) and iron and steel mills (NAICS 33111) from all analyses since price movements in these sectors are driven mostly by global commodity prices.

$\beta_{h,services}$ are depicted in the top right and the bottom left panels of Figure 6. We find that pass-through in the manufacturing sector is insignificant at all horizons. In contrast, pass-through in services is positive and significant.

Table 2 presents the detailed regression coefficients underlying Figure 6 for one specific horizon, $h = 8$. We will use this horizon as our baseline for all regressions, since aggregate pass-through from wages to prices peaks at 8 quarters for the PPI as shown in Figure 5b. Column 1 shows that over an eight quarter period the pass-through from wage changes to price changes is about 0.12. As expected, an increase in productivity has a negative effect on price changes. A 10% increase in productivity translates to a 1.0% decline in price growth. Column 2 mirrors panels (b) and (c) of Figure 6 and includes two separate coefficients for wage growth in the manufacturing and in the services sectors. These terms are computed as $\Delta \ln(w_{it})$ times a dummy for whether the industry is a manufacturing or a service industry. We do not control for TFP in Column 2, and add it in in Column 3 to analyze how productivity growth affects the pass-through coefficient. In both regressions, we find that the correlation between wage changes and price changes is insignificant in the manufacturing sector, both economically and statistically, and about 0.19 in services, confirming our earlier finding. Importantly, the pass-through of wages to prices is relatively unchanged when controlling for productivity.

One concern is that a wage shock can induce a dynamic path of wages, generating serial correlation, which could confound our estimates of the pass-through of a wage shock to prices. To address this concern, we construct the impulse response function of a change in wages on prices using an instrumental variables local projection (IV-LP) approach (e.g., Ramey (2016)). This approach was first developed in the government spending literature to compute the impact of a fiscal shock along the entire path of responses (see Mountford and Uhlig (2009)).[13] We present the results in Appendix E. We find that our findings are robust to using this methodology. In particular, we still find zero and insignificant pass-through in manufacturing and positive significant pass-through in services.

In our theoretical framework, we have shown that wage changes translate to a price change proportional to the industry's labor share, α. Through the lens of our model, the lower pass-through estimates for manufacturing in Columns 1–3 could reflect the differences in labor share across industries rather than differences in pricing behavior. To examine this possibility, we replace wage growth with the interaction of wage growth with the industry's labor share (with and without controlling for TFP). For manufacturing, we calculate the labor share in each industry as the industry's payroll divided by its total shipments in a

[13] The approach has since been used in other contexts, see Fieldhouse et al. (2018), Nekarda and Ramey (2020), Barnichon and Mesters (2021).

Table 2: Pass-Through Regressions for Manufacturing versus Services ($h = 8$)

	No Labor Share			Labor Share		
Δ PPI	(1) Aggregate	(2) No TFP	(3) With TFP	(4) Aggregate	(5) No TFP	(6) With TFP
ΔWage	0.118***					
	(0.0293)					
ΔTFP	-0.102***		-0.0877***	-0.0982***		-0.0928***
	(0.0329)		(0.0303)	(0.0319)		(0.0308)
ΔWage Manuf		-0.0389	-0.0173			
		(0.0253)	(0.0259)			
ΔWage Services		0.209***	0.193***			
		(0.0405)	(0.0387)			
ΔWage × LS				0.466***		
				(0.130)		
ΔWage Manuf × LS					-0.311**	-0.124
					(0.151)	(0.142)
ΔWage Services × LS					0.585***	0.520***
					(0.159)	(0.142)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0384	0.0379	0.0474	0.0369	0.0280	0.0385
Observations	12010	12010	12010	12010	12010	12010

Note: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (16), where the changes in wages, in TFP, and in the PPI are computed over an 8-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results. Columns 2 and 3 present the regression where we interact the change in wages with a dummy for the manufacturing sector and a dummy for the services sector, respectively. We exclude the change in TFP in column 2 and include it in column 3. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. These regressions also include a control for the labor share in levels, omitted from the table for simplicity. R-squared is the Within R-squared excluding fixed effects.

given year from the Annual Survey of Manufacturers (ASM) from 2003-2016. For non-manufacturing industries, we calculate the labor share as total payroll divided by sales from the censuses in 2002, 2007, and 2012, and assume that the labor shares remain constant until a new data release is available. We apply the labor share of a given year to all quarters of that year. We then estimate

$$\Delta_{t-h,t} \ln(p_{it}) = \beta\alpha_{it}\Delta_{t-h,t} \ln(w_{it}) + \psi\alpha_{it} + \gamma X_{it} + \delta_i + \rho_t + \epsilon_{it}, \tag{17}$$

where α_{it} is industry i's labor share in quarter t. This regression controls for heterogeneity in labor shares across industries. If pass-through in each industry was equal to its labor share, then the estimated coefficient β would be equal to one.

The results presented in Columns 4, 5 and 6 show that the lower pass-through in manufacturing is not due to a lower labor share in that sector. When we do not differentiate between manufacturing and services, we find a pass-through of 47% in column 4. When we estimate them separately, we find a pass-through of 59% in services (when controlling for productivity), implying that a 10% increase in labor costs is associated with a 5.9% increase in service prices in an industry with a labor share of one. The pass-through in manufacturing is still estimated to be small and insignificant.

In Appendix F, we present various robustness analyses. We show that the results are similar for $h = 4$ and $h = 12$; when the regression is not weighted by sales in 2012; and when we exclude time or industry fixed effects. For the manufacturing sector, we also consider an alternative measure of the labor share and compute the labor share as total payroll divided by value added.[14] Results for manufacturing are similar when we use this alternative labor share. We also consider an instrumental variables approach using job-to-job transitions as a proxy for a cost push shock to the firm in Appendix G. This approach isolates the *inflationary component of wage growth*, and measures the response of prices to a cost-push shock identified from job-to-job transitions. We find that cost-push shocks pass through to prices one-for-one in service-producing industries, whereas there is little or no pass-through in manufacturing.

3.3 Pass-Through in Manufacturing Over Time: 1993-2016

Our aggregate analysis has shown that the behavior of goods inflation changed after 2000 accounting for around half of the missing inflation in the 2003-2007 and 2009-2020 expansions. To connect the missing goods inflation to low pass-through in manufacturing, we now focus on estimating the time trend in manufacturing pass-through. While the PPI data are only available from 2003 onward for most service-providing industries, a longer time series going back to 1993 exists for manufacturing industries. For this purpose, we extend our concordance of 5-digit NAICS industries back to that year. We use only manufacturing industries and estimate pass-through coefficients for different time periods using the specification in (16). We compare the pre-2003 period to the period from 2003 onwards, based on our finding of a structural break in 2002/Q4 in the wage-price relationship in the aggregate PPI data above.

Table 3 presents our findings for $h = 8$. We continue to report estimates both without and

[14] Value added is not available for the services sector and hence a corresponding labor share cannot be computed for that sector.

Table 3: Pass-Through Regressions in Manufacturing ($h = 8$)

	No Labor Share		Labor Share	
	(1)	(2)	(3)	(4)
Δ PPI	All	Pre/Post	All	Pre/Post
Δ Wage	0.0118			
	(0.0223)			
Δ TFP	-0.185***	-0.180***	-0.206***	-0.201***
	(0.0201)	(0.0193)	(0.0218)	(0.0209)
Δ Wage × Pre-2003		0.0788***		
		(0.0239)		
Δ Wage × Post-2003		-0.0478		
		(0.0293)		
Δ Wage × LS			0.200	
			(0.175)	
Δ Wage × LS × Pre-2003				0.501**
				(0.217)
Δ Wage × LS × Post-2003				-0.146
				(0.259)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
R-squared	0.0466	0.0451	0.0581	0.0562
Observations	11922	11922	11922	11922

Note: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (18), where the changes in wages, in TFP, and in the PPI are computed over an 8-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results without the interaction for the pre- and post-period. Column 2 shows the results with the interaction. Columns 3-4 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. These regressions also include a control for the labor share in levels, omitted from the table for simplicity. R-squared is the Within R-squared excluding fixed effects.

with the labor share interaction. The results without the interaction are useful to quantify how much prices would change for a one percent change in wages in an industry with the average labor share, incorporating the effect of the labor share on pass-through. In that sense, these estimates provide a *reduced form* estimate of the relationship between wages and prices. Instead, the results with the labor share interaction highlight by how much prices would move with a change in wages in a hypothetical industry with a labor share of one. This estimate therefore removes the heterogeneity in the labor share across industries. To recover the magnitude of *actual* pass-through from wages to prices for a given industry, one would need to multiply the pass-through coefficient by that industry's labor share.

The first column of Table 3 shows that over the extended period, the average pass-through is positive but very small in manufacturing. In the second column, we allow the pass-through coe□cient to vary over time. Specifically, we estimate the e□ect for the periods before and after 2003 by interacting the wage change with a dummy for these periods

$$\Delta_{t-h,t}\ln(p_{it}) = \beta_{1,h}\Delta_{t-h,t}\ln(w_{it})\mathbb{I}_{t<2003} + \beta_{2,h}\Delta_{t-h,t}\ln(w_{it})\mathbb{I}_{t\geq 2003} + \gamma X_{it} + \delta_i + \rho_t + \epsilon_{it}, \quad (18)$$

where $\mathbb{I}_{t<2003}$ is a dummy that is equal to one if t is prior to 2003, and $\mathbb{I}_{t\geq 2003}$ is defined analogously for the period from 2003 onwards. Our results indicate a notable change in the price pass-through over time. For the period prior to 2003, increases in wages passed through to prices. The pass-through declined substantially to essentially zero after 2003. The results are more stark when we interact the change in wages with the labor share of the industry in column 4. We obtain the labor share for all manufacturing industries from the ASM for 1997-2016, and apply the labor share of 1997 in earlier years. We find a pass-through of 50% per unit of labor for the pre-2003 period while we estimate no pass-though for the later period. This specification shows that the decline in pass-through is not accounted for by the decline in the labor share of the manufacturing sector. The finding is also consistent with our aggregate local projections above which showed a sharp decline in pass-through in the early 2000s. Appendix F shows that the results are similar for $h = 4$ or $h = 12$.

3.4 Taking Stock

Our empirical analysis established a number of important facts. First, we estimate a high pass-through from labor costs to producer prices in the services sector in the 2003-2016 period. Our estimate for pass-through from wages to prices in the services sector is around 50 percent per unit of labor. Second, we estimate very little or no pass-through from labor costs to prices in manufacturing in the post-2003 period. Third, our data analysis extended to the 1993-2016 period for the manufacturing sector shows that this was not the case in the pre-2003 period. Pass-through in manufacturing was positive around 50 percent per unit of labor in the 1993-2003 period—similar to what we found for services—but vanished in the post-2003 period. In the next section, we evaluate potential explanations for this change.

4 Why Did Pass-Through Disappear in Manufacturing?

There are various changes in the U.S. economy that coincided with the change in wage-to-price pass-through that we document in the aggregate and industry-level data. Motivated by our theoretical analysis, we consider the roles of two notable changes. The first is the rise in import penetration. With increasing import penetration into the U.S. economy, an increasingly higher fraction of domestic sales are accounted for by imported goods. The second is the rising concentration in product markets (and to a lesser extent in labor markets) with a small number of firms accounting for a higher fraction of total sales or employment. Both trends are quite prominent and could have potentially affected firms' pricing behavior. Our theoretical model captures the mechanism through which they affect pricing behavior of firms.

A substantial literature has documented an increase in import competition in the U.S. manufacturing sector since the 1990s, in particular associated with China's WTO entry in the early 2000s (e.g., Autor et al. (2013)). This literature has documented substantial effects of import competition on U.S. employment and other outcomes (e.g., Pierce and Schott (2016)). A commonly used measure to quantify import competition is the *import penetration* which measures the fraction of domestic consumption of manufacturing goods that is imported. Figure 7a shows the evolution of import penetration in the average 5-digit NAICS industry in our sample in the U.S. manufacturing sector over time. While in the early 1990s imports accounted for only about 15% of sales in the average manufacturing industry in the U.S., imports rose to more than 30% of manufacturing sales in 2016. As highlighted by Theorem 3.1, a larger number of foreign firms not subject to U.S. wage shocks would make an industry's price index less responsive to wage changes. Given its striking rise, import penetration therefore could account for the declining pass-through in manufacturing that we documented in the previous section.

A second important change in the U.S. economy is the rising market concentration as documented by Autor et al. (2020). Figure 7b shows the average sales share of the top 20 firms in the manufacturing sector.[15] There was a gradual increase in the concentration of sales in top 20 firms over time. We obtain the concentration measures from the Census of Manufactures, and interpolate between census years (1997, 2002, 2007, 2012, and 2017) using linear interpolation.[16]

Rising market concentration could also potentially affect firms' pricing decisions. As highlighted by Theorem 3.1, decreasing competition causes firms to internalize more the strategic nature of the pricing game and to focus more on their price relative to the industry's price index. As a result, increasing concentration could generate declining pass-through.

We use our industry-level data to examine whether the *import penetration channel* and the *market concentration channel* affected wage-to-price pass-through in the manufacturing

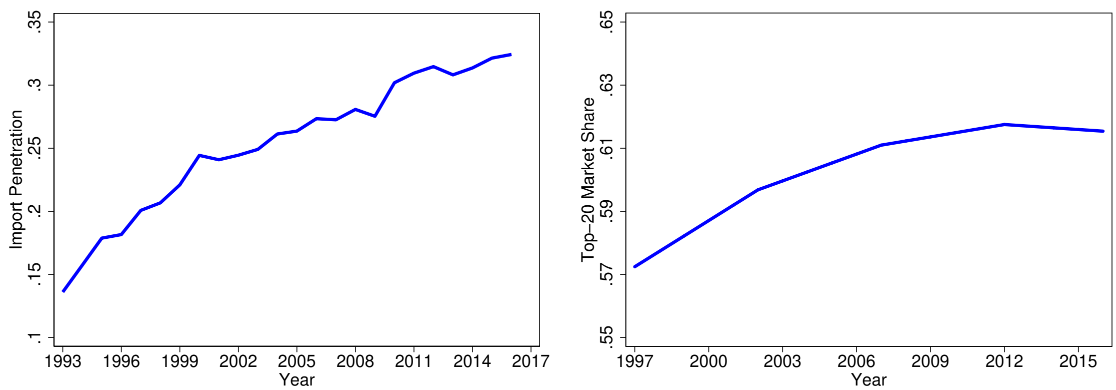
[15] Figures H.1a and H.1b in Appendix H show that the patterns are similar for the sales share of the top 4 firms and the HHI.

[16] We do not include data from the 1992 census since it is only reported on an SIC basis, and concentration measures are difficult to map from SIC to NAICS industries

Figure 7: Rising Import Penetration and Concentration in the Manufacturing Sector

(a) Import Penetration

(b) Top-20 Concentration



Note: The left panel shows the average of import penetration across 5-digit manufacturing industries in our sample. Import penetration is computed as imports divided by U.S. firms' shipments plus imports minus exports. Annual imports and exports of each industry are from the U.S. Census Bureau. Shipments are from the Annual Survey of Manufacturing and from the economic censuses. The right panel shows the average market share of the top-20 firms in the manufacturing industries in our sample, obtained from the Census of Manufactures. We interpolate between census years (1997, 2002, 2007, 2012, and 2017) using linear interpolation. Earlier data is unavailable on a NAICS basis.

sector.

4.1 The Role of the Rise in Import Penetration

We examine the *import penetration channel* using extensive cross-sectional data. In particular, we investigate whether pass-through is lower in industries with a higher exposure to trade. We proxy for trade competition in an industry with the change in import penetration since 1997, similar to the measure in Autor et al. (2013). Specifically, we compute the change in import penetration of industry i as

$$\Delta IP_{i,97,t} = \frac{\Delta_{1997,t}\text{Imports}_{it}}{\text{Sales}_{i,1997} - \text{Exports}_{i,1997} + \text{Imports}_{i,1997}}, \tag{19}$$

where Imports_{it} are imports by industry i in year t, Exports_{it} are the industry's total exports, Sales_{it} are the total sales in that industry, and $\Delta_{1997,t}\text{Imports}_{it}$ is the change in imports between 1997 and year t.[17] We obtain imports and exports for each NAICS industry each year from the U.S. Census Bureau, available via Peter Schott's website.[18] Total sales for each industry are obtained from the ASM. Additional details are in Appendix D. A higher

[17] In a slight abuse of notation. We do not have quarterly import penetration data.

[18] https://sompks4.github.io/sub_data.html

import penetration implies that a larger share of an industry's U.S. sales is accounted for by imports, suggesting that U.S. firms in that sector are heavily exposed to foreign competition.

We interact our measure of import competition in each industry with the wage change. We then estimate the modified pass-through regression

$$\Delta_{t-h,t}\ln(p_{it}) = \beta_0\Delta_{t-h,t}\ln(w_{it}) + \beta_1\Delta_{t-h,t}\ln(w_{it}) * \Delta IP_{i,97,t} + \phi\Delta IP_{i,97,t} + \gamma X_{it} + \rho_t + \epsilon_{it}. \quad (20)$$

The first column of Table 4 presents the results from this regression for $h = 8$ quarters. We find that a greater increase in import penetration significantly lowers pass-through in a given industry. Going from the 25th to the 75th percentile of the change in import penetration since 1997 (from 1 to 21 percentage points) would lower pass-through from wages to prices from about 3.7% to essentially zero. Since our regression incorporates time fixed effects and therefore picks up the aggregate increase in import penetration, this finding does not simply reflect our earlier result that pass-through in manufacturing fell over time, while at the same time import penetration rose. Instead, the results indicate that industries that experience high import penetration exhibit relatively lower pass-through.

In column 2, we construct a dummy variable for whether an industry's import penetration is above the 50th percentile of import penetration across all industries. We also construct the complementary dummy for industries below the 50th percentile. In column 3 we run a similar regression with dummies indicating whether an industry is above or below the 75th percentile. The point estimates show that industries with a low level of import penetration exhibit a significantly positive pass-through from wages to prices. In contrast, high import penetration industries have a pass-through that is statistically indistinguishable from zero.

Columns 4 to 6 redo the analysis using the interaction of the wage change with the labor share. The regression now also includes a control for the labor share by itself and the labor share interacted with ΔIP, which we omit for brevity from the reported results. From column 4, we find that going from the 25th to the 75th percentile of the change in import penetration since 1997 would lower pass-through from wages to prices per unit of labor from about 38.5% to 15.3%. Columns 5 and 6 show that pass-through is strong and positive in industries with a low change in import penetration, but insignificant and high import penetration industries.

Overall, our results support the conjecture of Theorem 3.1. Industries that are exposed to higher degree of competition from abroad do not raise their prices as much in response to increasing wages, and therefore exhibit a lower increase in price inflation. As import penetration has risen significantly over the last decades, pass-through in manufacturing overall has declined. In Appendix H, we show that the results are robust to different choices of lag

Table 4: Pass-Through and Import Penetration in Manufacturing ($h = 8$)

	No Labor Share			Labor Share		
Δ PPI	(1) Δ IP	(2) 50th Pct	(3) 75th Pct	(4) Δ IP	(5) 50th Pct	(6) 75th Pct
Δ Wage	0.0385*					
	(0.0201)					
Δ TFP	-0.189***	-0.192***	-0.183***	-0.215***	-0.210***	-0.210***
	(0.0208)	(0.0209)	(0.0207)	(0.0214)	(0.0226)	(0.0207)
Δ Wage $\times$ Δ IP	-0.160**					
	(0.0708)					
Δ Wage $\times$ Low IP		0.0623**	0.0408**			
		(0.0241)	(0.0193)			
Δ Wage $\times$ High IP		-0.0321	-0.0545			
		(0.0309)	(0.0434)			
Δ Wage $\times$ LS				0.396**		
				(0.158)		
Δ Wage $\times$ LS $\times$ Δ IP				-1.136***		
				(0.357)		
Δ Wage $\times$ LS $\times$ Low IP					0.641***	0.498***
					(0.190)	(0.173)
Δ Wage $\times$ LS $\times$ High IP					-0.192	-0.404
					(0.228)	(0.325)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0528	0.0520	0.0491	0.0668	0.0623	0.0634
Observations	11353	11353	11353	11353	11353	11353

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (20), where the changes in wages, in TFP, and in the PPI are computed over an 8-quarter period, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results from specification (20). We omit the coefficient on ΔIP by itself for brevity. In column 2, we replace the continuous measure of IP by a dummy indicating whether an industry's ΔIP in the given year is above the median of ΔIP, and include two dummies for below and above median IP interacted with the wage change. Column 3 is analogous but using the 75th percentile. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. The regression in column 4 includes a control for the labor share by itself, the labor share interacted with ΔIP, and ΔIP, which we omit for brevity. We similarly include in columns 5-6 the labor share interacted with dummies for above and below median IP and one of these dummies by itself. R-squared is the Within R-squared excluding fixed effects.

length or to using import penetration with respect to China only.

4.2 The Role of the Rise in Market Concentration

The increase in import concentration in the U.S. coincided with the rise in market concentration which we refer to as the *market concentration channel*. Various recent papers have

Table 5: Measures of Concentration in 1997 and 2016

	1997	2016
Top-4 Sales Share	30.0%	33.4%
Top-20 Sales Share	57.2%	61.5%
Sales HHI	0.044	0.049
	1997	2014
Top-4 Employment Share	25.2%	28.3%
Top-20 Employment Share	47.9%	50.1%
Employment HHI	0.037	0.052

Notes: The top panel presents average sales concentration across the manufacturing industries in our sample in two different years. The bottom panel presents employment concentration from the NETS database. Market shares are computed as a firm's share of employment. Employment concentration in 2014 is the latest year available to the authors in NETS.

focused on the role of rising market concentration on the aggregate economy and connected the rise in market power to the increase in markups and the decline in the labor share.[19] Our theory above suggests that a rise in concentration should lead to a decline in wage-price pass-through.

We evaluate the effect of rising market concentration on pass-through from wages to prices using different measures of sales concentration. In particular, we use three measures: the share of sales of the top-4 firms and of the top-20 firms in an industry, and the HHI of the 50 largest firms. All three of these measures are obtained from the Census of Manufactures in 1997, 2002, 2007, 2012, and 2017, and linearly interpolated in between census years. As an alternative measure of concentration, we also use employment concentration, which we obtain from Walls & Associates' National Establishment Time-Series (NETS) database for 1993-2014. NETS contains an annual time series of establishment sales and employment, among other measures, for more than 40 million establishments collected by Dun and Bradstreet.[20] We compute the share of employees working for the top-4 and top-20 employers, respectively, in our data in each year, and similarly compute an employment HHI. Table 5 shows the increase in concentration measures from 1997 to 2016. The increase is more pronounced for sales-based measures as discussed in Hershbein et al. (2018).

We estimate the following specification

$$\Delta_{t-h,t}\ln(p_{it}) = \beta_0\Delta_{t-h,t}\ln(w_{it}) + \beta_1\Delta_{t-h,t}\ln(w_{it}) * C_{it} + \phi C_{it} + \gamma X_{it} + \delta_i + \rho_t + \epsilon_{it}, \quad (21)$$

where C_{it} is the measure of concentration used. We report the results in Table 6 using different measures of market concentration. Since we only have concentration measures

[19] See for example De Loecker et al. (2020) and Autor et al. (2020)

[20] Recent work using these data is for example Rossi-Hansberg et al. (2018)

for 1997-2016, we run the regression only for this shorter time period. As reported in the table, the effect of market concentration is negative and significant for all measures of market concentration. For example, using the top-4 market share of sales as measure of concentration, column 1 indicates that a 1% wage increase translates into a 0.13% price increase in an industry with zero concentration. In comparison, an industry with top-4 market concentration of nearly 50%, at the 75th percentile of concentration across industries, would raise prices in response to the same shock by only about 0.06%. Coupled with the observation that concentration measures increased over time as we documented in Table 5, our findings suggest that increasing market concentration has weakened the pass-through from wages to prices. This finding is consistent with Theorem 3.1. Columns 2 and 3 show similar results for the other concentration measures.

Columns 4-6 present the estimates when we interact wage changes with the labor share. The regression now also includes a control for the labor share by itself and the labor share interacted with the concentration measure, which we omit for brevity from the reported results. Column 4 shows that going from zero concentration to a top-4 market concentration of 50% would lower pass-through from wages to prices per unit of labor from 88.2% to zero. Columns 5 and 6 confirm these results for the other concentration measures.

Equation (15) from our theoretical framework is key to understand the intuition of why market concentration can also lead to lower pass-through. When firms set high markups, they are able to at least partially absorb cost-push shocks into their markup without passing through the rising costs to consumers. Firms take into account that by raising their price they lose market share to competitors that did not experience the same shock. As a result, firms absorb part of the shock into their markup, changing their price by less in response to input shocks. In a relatively competitive market there is little room for firms to absorb cost-push shocks, and firms therefore pass them through more fully.

In Appendix H, we show that the results are robust to different choices of lag length or to using employment concentration as measure of concentration.

4.3 Import Penetration versus Market Concentration

Our theoretical and empirical analyses provide strong support for rising import penetration and increasing market concentration as sources of declining pass-through. We now consider both of them together and their contribution to the decline in pass-through.

We estimate a specification that combines time-varying pass-through with both import

Table 6: Pass-Through and Sales Concentration in Manufacturing (1993-2016, $h = 8$)

	No Labor Share			Labor Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ PPI	Top-4	Top-20	HHI	Top-4	Top-20	HHI
Δ Wage	0.130**	0.278***	0.0682			
	(0.0505)	(0.0763)	(0.0419)			
Δ TFP	-0.199***	-0.202***	-0.203***	-0.211***	-0.212***	-0.220***
	(0.0237)	(0.0232)	(0.0246)	(0.0245)	(0.0241)	(0.0257)
Δ Wage × Conc	-0.249***	-0.367***	-0.637**			
	(0.0729)	(0.0892)	(0.287)			
Δ Wage × LS				0.882***	1.499***	0.515**
				(0.296)	(0.372)	(0.246)
Δ Wage × LS × Conc				-2.000***	-2.213***	-5.477**
				(0.576)	(0.497)	(2.209)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0573	0.0598	0.0557	0.0657	0.0676	0.0661
Observations	10042	10042	9586	10042	10042	9586

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. Conc refers to the concentration measure listed in the column header. Top-4 refers to the sales share of the top 4 firms. Top-20 is defined analogously. HHI is the Herfindahl-Hirschmann Index defined over the top 50 firms in the industry. The table presents the estimates from specification (21), where the changes in wages, in TFP, and in the PPI are computed over an 8-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since sales concentration is only available in census years (1997, 2002, 2007, 2012, 2017), we construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2016. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Columns 1-3 present the baseline regression results from specification (21) using the three concentration measures. We omit the coefficient on $Conc$ by itself for brevity. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. The regressions include a control for the labor share by itself, the labor share interacted with $Conc$, and $Conc$ by itself, which we omit for brevity. R-squared is the Within R-squared excluding fixed effects.

penetration and concentration:

$$\Delta_{t-h,t}\ln(p_{it}) = \beta_0\Delta_{t-h,t}\ln(w_{it})\mathbb{I}_{t<2003} + \beta_1\Delta_{t-h,t}\ln(w_{it})\mathbb{I}_{t\geq 2003} + \beta_2\Delta_{t-h,t}\ln(w_{it}) * \Delta IP_{i,97,t} + \beta_3\Delta_{t-h,t}\ln(w_{it}) * C_{it} + \phi_1\Delta IP_{i,97,t} + \phi_2 C_{it} + \gamma X_{it} + \delta_i + \rho_t + \epsilon_{it}, \quad (22)$$

where X_{it} includes all the relevant interaction terms between the variables of interest. Table 7 presents the results for $h = 8$. The first column re-runs the results from above including only the time-varying pass-through, for the shorter period 1997-2016. Column 2 considers only import penetration. Column 3 considers only concentration. Finally, column 4 combines both explanations. Once both mechanisms are taken into account, we recover an economically and statistically significant pass-through coefficient in the post-2003 period consistent with the implications of our model.

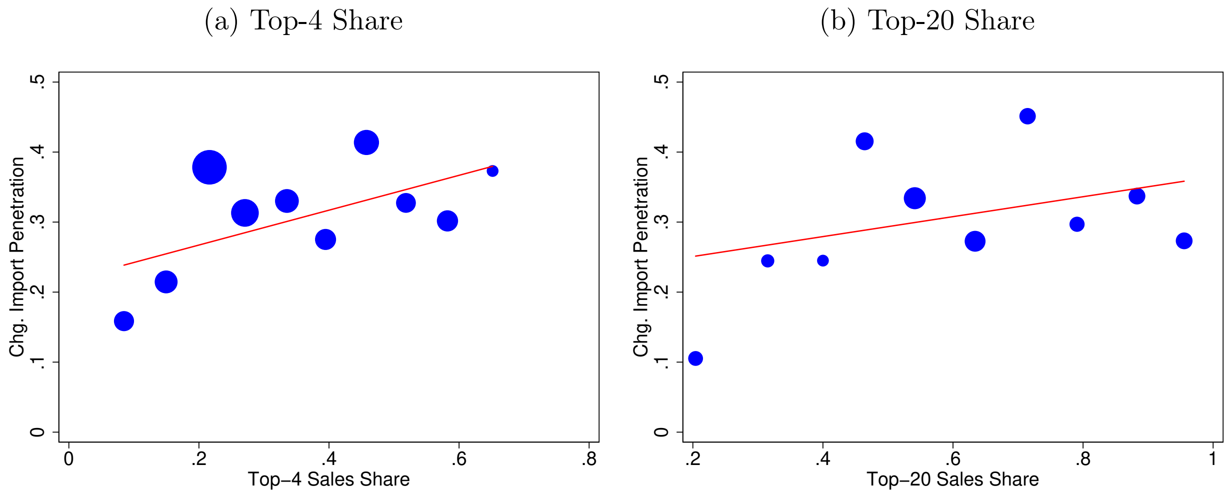
Table 7: Pass-Through Regressions: Import Penetration versus Concentration ($h = 8$)

Δ PPI	(1) Baseline	(2) IP Only	(3) Conc Only	(4) Both
Δ Wage × LS × Pre-2003	0.671***	0.820***	2.022***	1.957***
	(0.250)	(0.254)	(0.419)	(0.434)
Δ Wage × LS × Post-2003	-0.282	-0.106	1.198**	1.167**
	(0.262)	(0.264)	(0.490)	(0.481)
Δ TFP	-0.205***	-0.215***	-0.208***	-0.217***
	(0.0236)	(0.0227)	(0.0232)	(0.0224)
Δ Wage × LS × Δ IP		-0.801**		-0.631*
		(0.374)		(0.377)
Δ Wage × LS × Conc			-2.391***	-2.096***
			(0.552)	(0.555)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
R-squared	0.0616	0.0686	0.0673	0.0740
Observations	10042	10042	10042	10042

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. LS refers to labor share. Conc refers to the market share of the top-20 firms. The table presents the estimates from specification (22), where the changes in wages, in TFP, and in the PPI are computed over an 8-quarter period, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. Since sales concentration is only available in census years (1997, 2002, 2007, 2012), we construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2012. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results from specification (22) excluding the terms involving IP or concentration, for the shorter time period 1997-2016. We omit the coefficient on the labor share for brevity. In column 2, we add the terms involving IP, omitting the terms on ΔIP by itself, the labor share, and on ΔIP times the labor share from the table for brevity. In column 3 we include only the terms involving concentration, omitting $Conc$ by itself, the labor share, and on $Conc$ times the labor share. In column 4 we finally add all terms involving IP and concentration. R-squared is the Within R-squared excluding fixed effects.

While we find negative effects of pass-through of both import penetration and market concentration, we can not necessarily identify their individual effects. Figures 8a and 8b show that import penetration and concentration are in fact positively related. In these figures, we sort all industries by their average market concentration over the period 1997-2016, and assign them to equally spaced buckets. We then take the average increase in import penetration between 1997 and 2016 across all industries in the bucket, and plot it against the average concentration. For the top-4 market share measure, we drop industries where the top four firms have a market share of more than 70% – these industries are small, and behave somewhat differently. The size of each bubble is proportional to the sales of each industry in 2012 from the Census of Manufactures. The figure highlights a positive relationship between market concentration and the growth in overall import penetration between 1997

Figure 8: Import Penetration versus Market Concentration



Note: The panels plot the change in import penetration between 1997 and 2016 against the average concentration over that period for groups of industries. The left panel uses the top-4 sales share, the right panel uses the top-20 sales share as concentration measure. We assign industries to ten groups based on their average concentration, where the groups are uniformly distributed between the minimum and the maximum level of concentration. We then compute the mean change in import penetration and the mean concentration for each group. The size of each circle is proportional to the total sales of the given industry group in 2012.

and 2016. Industries with a high average concentration also exhibit a significant increase in import competition. In Appendix H, we plot similar figures for import penetration with respect to China only and find similar results. This finding suggests that our two findings of import competition and concentration affecting pass-through are related, and provides further evidence in support of our Theorem 3.1. As documented by Amiti and Heise (2021), as foreign exporters entered U.S. markets and raised import penetration, many domestic firms exited, increasing U.S. domestic concentration. Through the lens of our model, the remaining large firms are able to charge relatively higher markups, but are forced to adjust these in response to wage shocks due to the increased competition from foreign firms in order to preserve market share.

4.4 Cross-Country Evidence

Since rising import penetration and increasing market concentration are affecting many countries, we expect to see a similar pattern in the cross-country data. While a detailed micro-data based analysis is beyond the scope of our paper, our analysis of core goods and services inflation in Canada, U.K., and the Eurozone show that these countries also experienced a growing disconnect between goods inflation and labor market conditions, (See

Appendix I). Since these countries have also been experiencing rising import competition and concentration, it is likely that the same forces are in at work in these countries.

5 Conclusions

In this paper, we have shown that a significant part of the missing inflation during the most recent expansions can be attributed to the lack of inflation in the goods-producing sector. We have traced this slowdown in goods inflation to a decline in the pass-through of wage shocks to prices in manufacturing. Motivated by our theory of price setting with variable markups, our empirical findings based on extensive industry-level data confirm that rising import competition and increasing market concentration are important drivers of this declining pass-through from labor costs to prices. In related work, Amiti and Heise (2021) show that rising import penetration caused domestic market concentration to increase.

Our paper complements the well-established literature on the role of anchoring of inflation expectations in explaining recent inflation dynamics such as Del Negro et al. (2015), Carvalho et al. (2017), Coibion and Gorodnichenko (2015), Crump et al. (2019), and Coibion et al. (2019). We document an additional channel operating via core goods inflation, which can account for the sluggishness of goods inflation relative to services inflation. This observation is also related to the flattening of the price Phillips Curve as discussed in Stock and Watson (2019). An open question remains to which extend import competition, rising market concentration, and inflation expectations interact—an issue we leave to future work.

Our findings have important implications for implementation of monetary policy. Central bankers typically view the declining unemployment rate as a precursor to rising inflation. We show that globalization and rising concentration alleviated the trade-off between unemployment and inflation. Declining unemployment and improving labor market conditions pose less of an inflation threat than before as is evident from the last decade. In addition, globalization of the inflation process increased the importance of coordination of monetary policy among central banks as emphasized by Obstfeld (2020).

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A Additional Aggregate Evidence

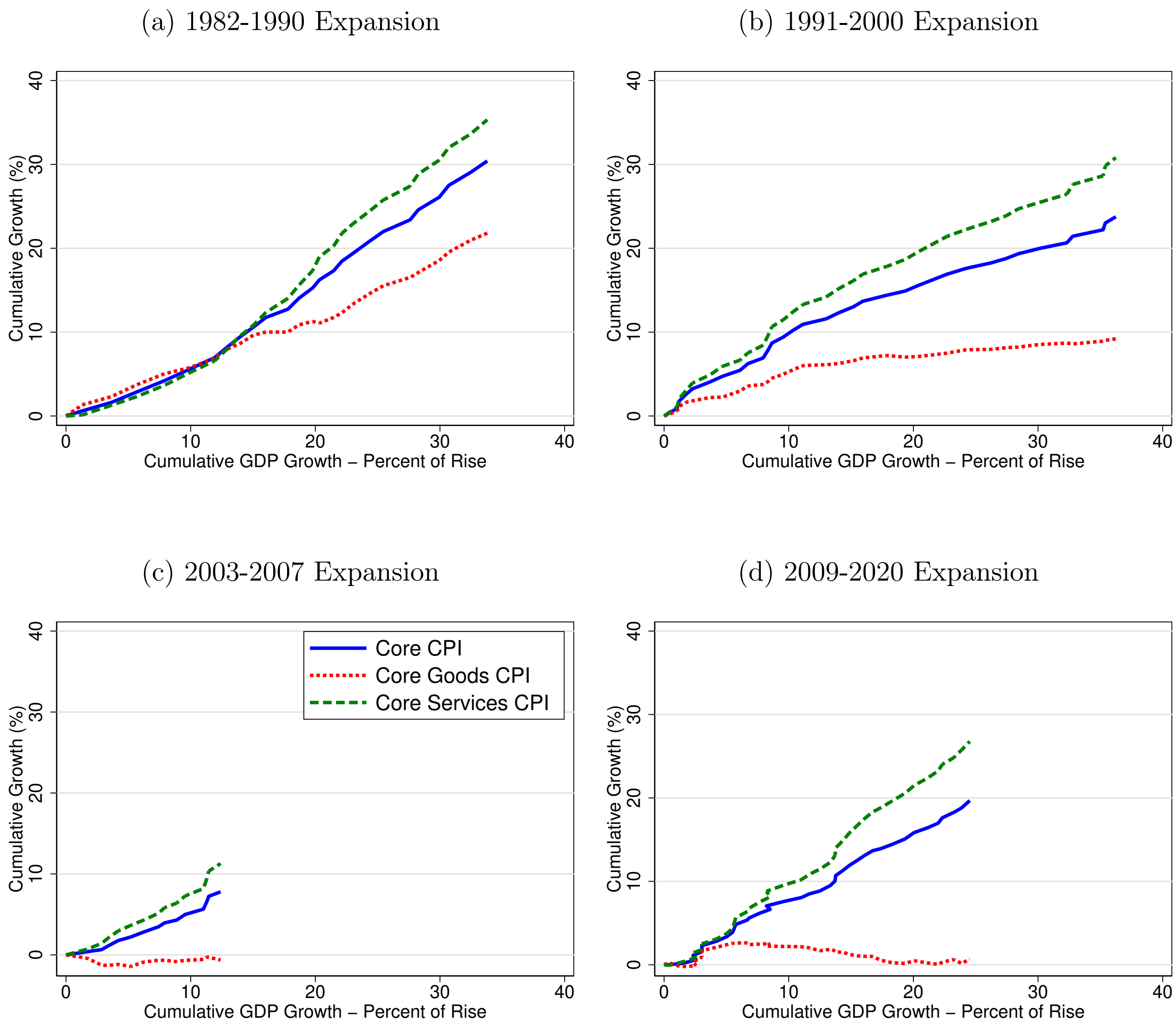
In this section, we show that the slow recovery of core goods inflation in recent recoveries also holds under alternative measures to the unemployment recovery gap. We also show that wage inflation in goods has remained steady, and that the pass-through results do not depend on including the unemployment gap in our regression specification.

Figure A.1 plots cumulative inflation against the cumulative GDP growth since peak unemployment in the preceding recession, rather than against the unemployment recovery gap as in the main text. We still find a dramatic slowdown in core goods inflation. In Figure A.2 we plot inflation against time and find a similar result. Figure A.3 plots inflation against the recovery gap in the employment-to-population ratio, calculated analogously to the measure using unemployment. The results are similar.

Figure A.4 shows the cumulative wage inflation against the cumulative GDP growth since peak unemployment in the preceding recession, rather than against the unemployment recovery gap as in the main text. Figure A.5 plots inflation against time since peak unemployment. We see a relatively similar wage inflation in the goods and in the services sector in all recoveries.

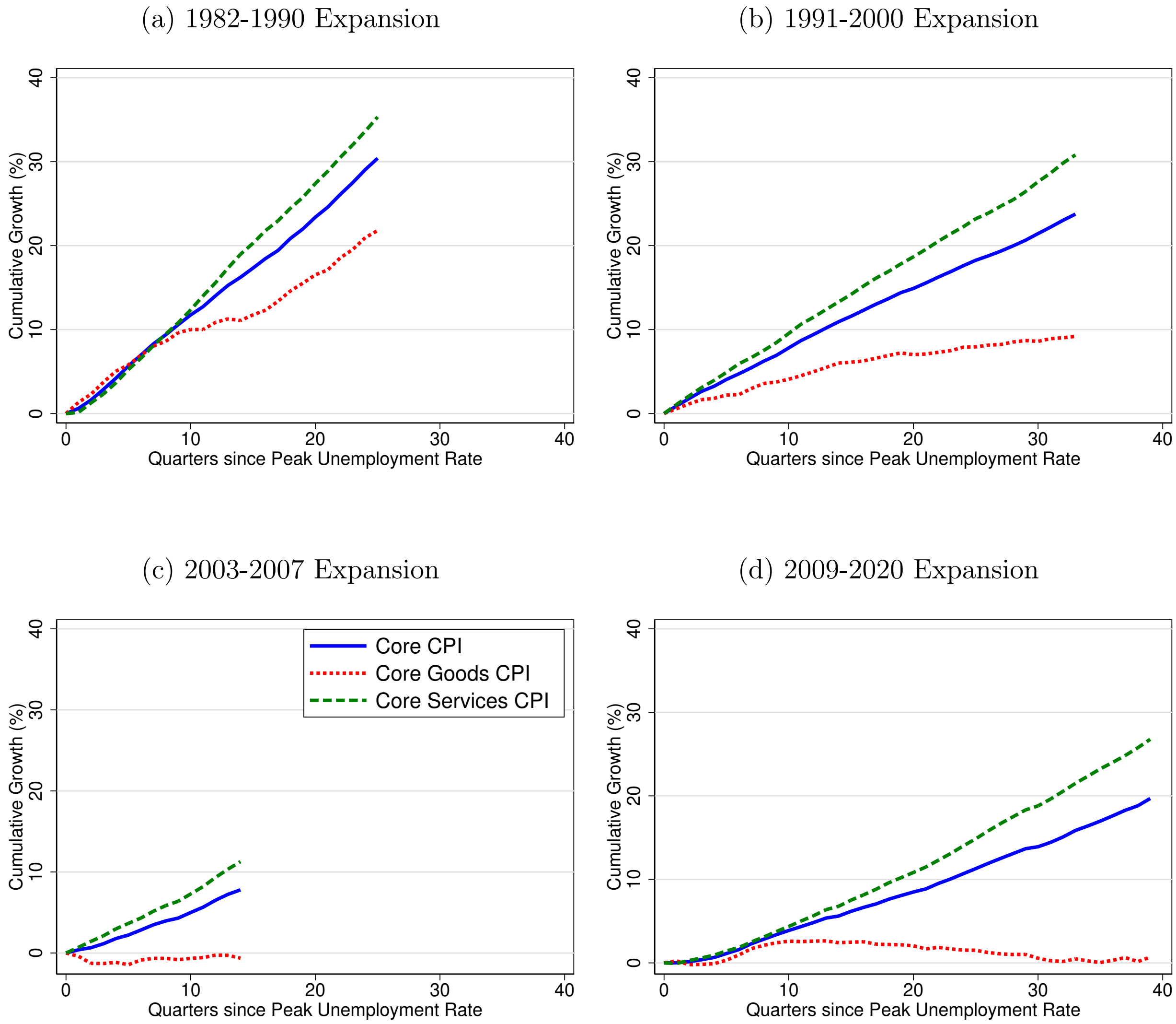
Finally, Figure A.6 runs the aggregate pass-through regressions (2) but without including the unemployment gap measure in the specification. We find impulse responses that are very similar to those in the main text.

Figure A.1: Inflation versus GDP Growth from Four Previous Recessions



Source: BLS and authors' calculations. Note: The blue line in each panel plots the cumulative core CPI inflation (all items less food and energy, seasonally adjusted) against cumulative GDP growth, starting at peak unemployment of a given recession. The red dotted line shows the core goods CPI (commodities less food and energy commodities, seasonally adjusted) and the green dashed line presents core services CPI (services less energy services, seasonally adjusted).

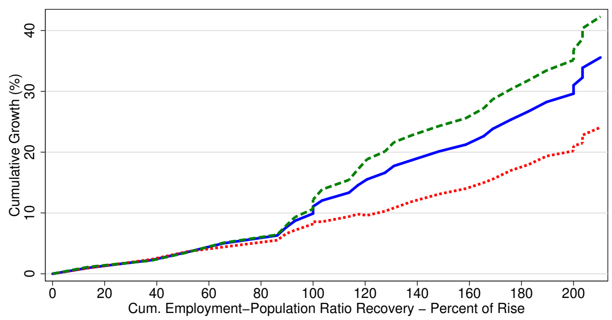
Figure A.2: Inflation from Four Previous Recessions



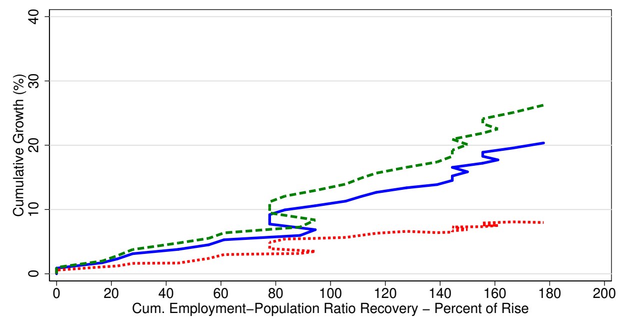
Source: BLS and authors' calculations. Note: The blue line in each panel plots the cumulative core CPI inflation (all items less food and energy, seasonally adjusted) against time, starting at peak unemployment of a given recession. The red dotted line shows the core goods CPI (commodities less food and energy commodities, seasonally adjusted) and the green dashed line presents core services CPI (services less energy services, seasonally adjusted).

Figure A.3: Inflation versus Employment-to-Population Ratio from Four Previous Recessions

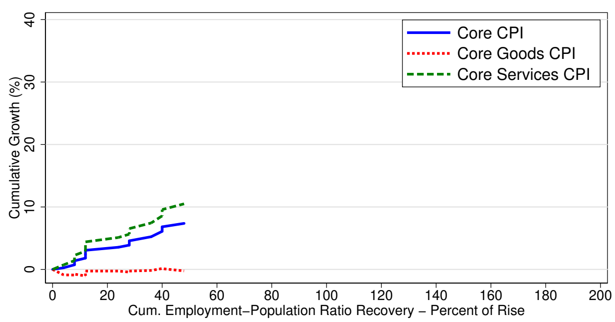
(a) 1982-1990 Expansion



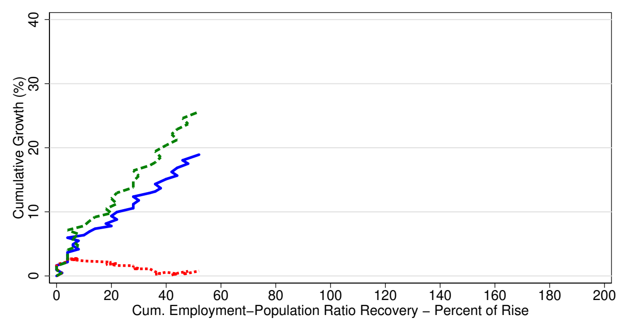
(b) 1991-2000 Expansion



(c) 2003-2007 Expansion



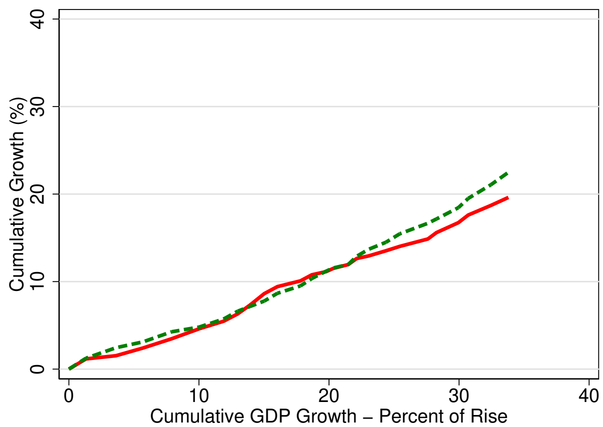
(d) 2009-2020 Expansion



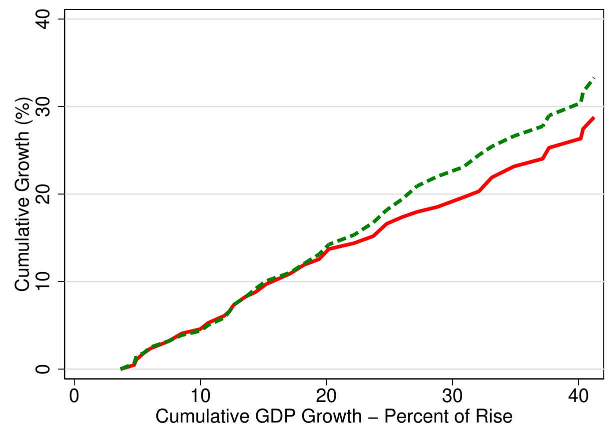
Source: BLS and authors' calculations. Note: The blue line in each panel plots the cumulative core CPI inflation (all items less food and energy, seasonally adjusted) against the Employment-to-Population Ratio Recovery Gap, defined analogously to the unemployment recovery gap in the text but using the employment-to-population ratio instead. The red dotted line shows the core goods CPI (commodities less food and energy commodities, seasonally adjusted) and the green dashed line presents core services CPI (services less energy services, seasonally adjusted).

Figure A.4: Wage Growth versus GDP Growth from Four Previous Recessions

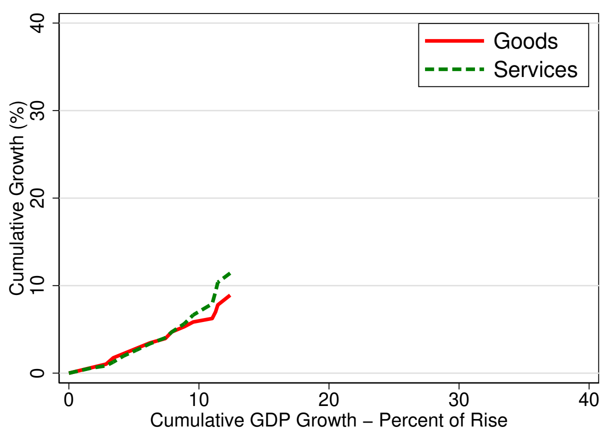
(a) 1982-1990 Expansion



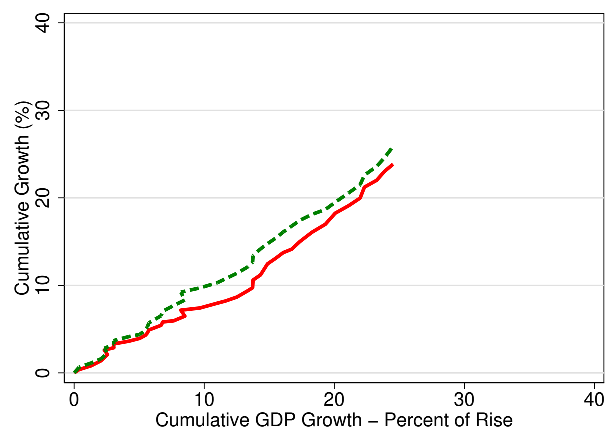
(b) 1991-2000 Expansion



(c) 2003-2007 Expansion

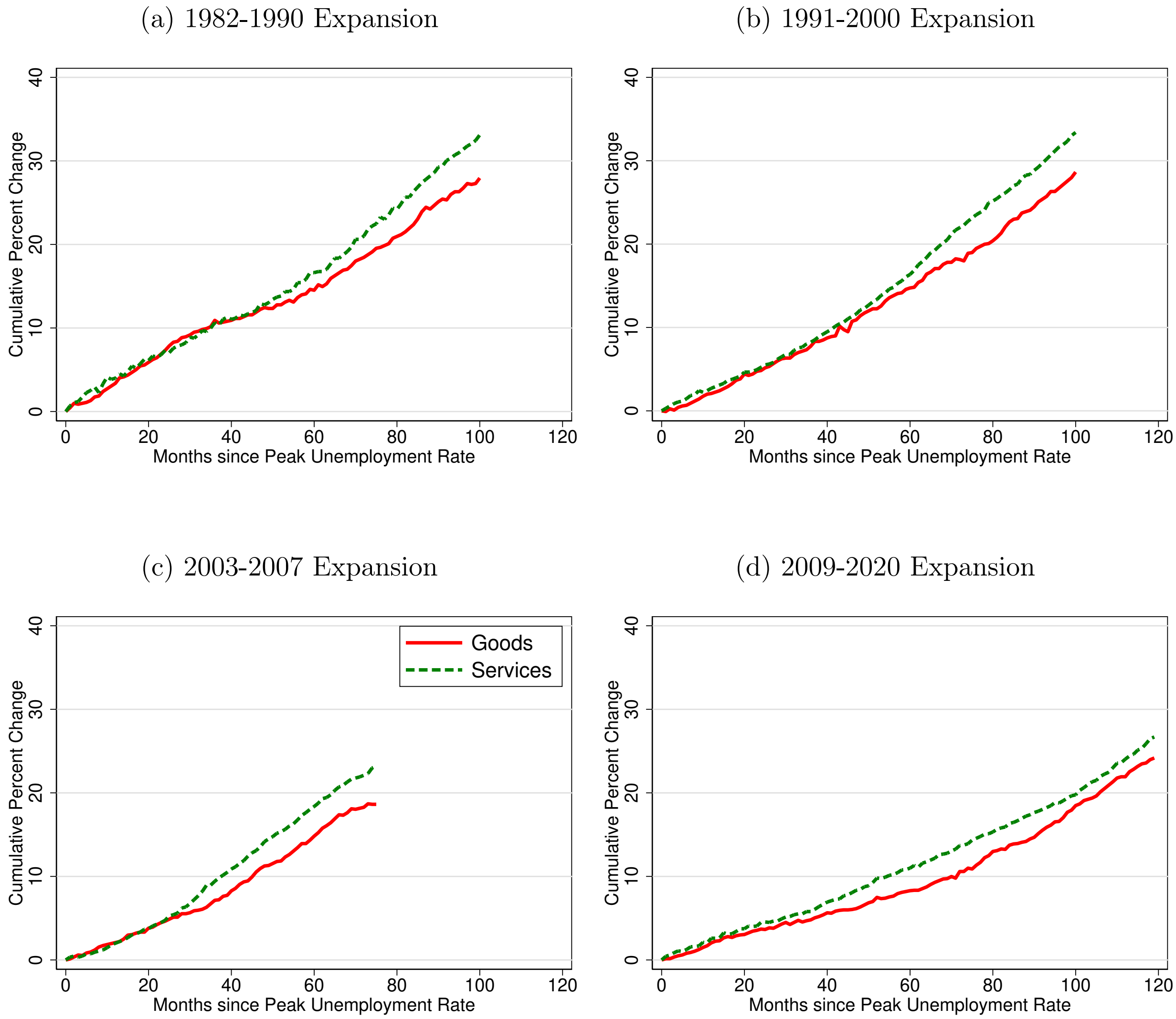


(d) 2009-2020 Expansion



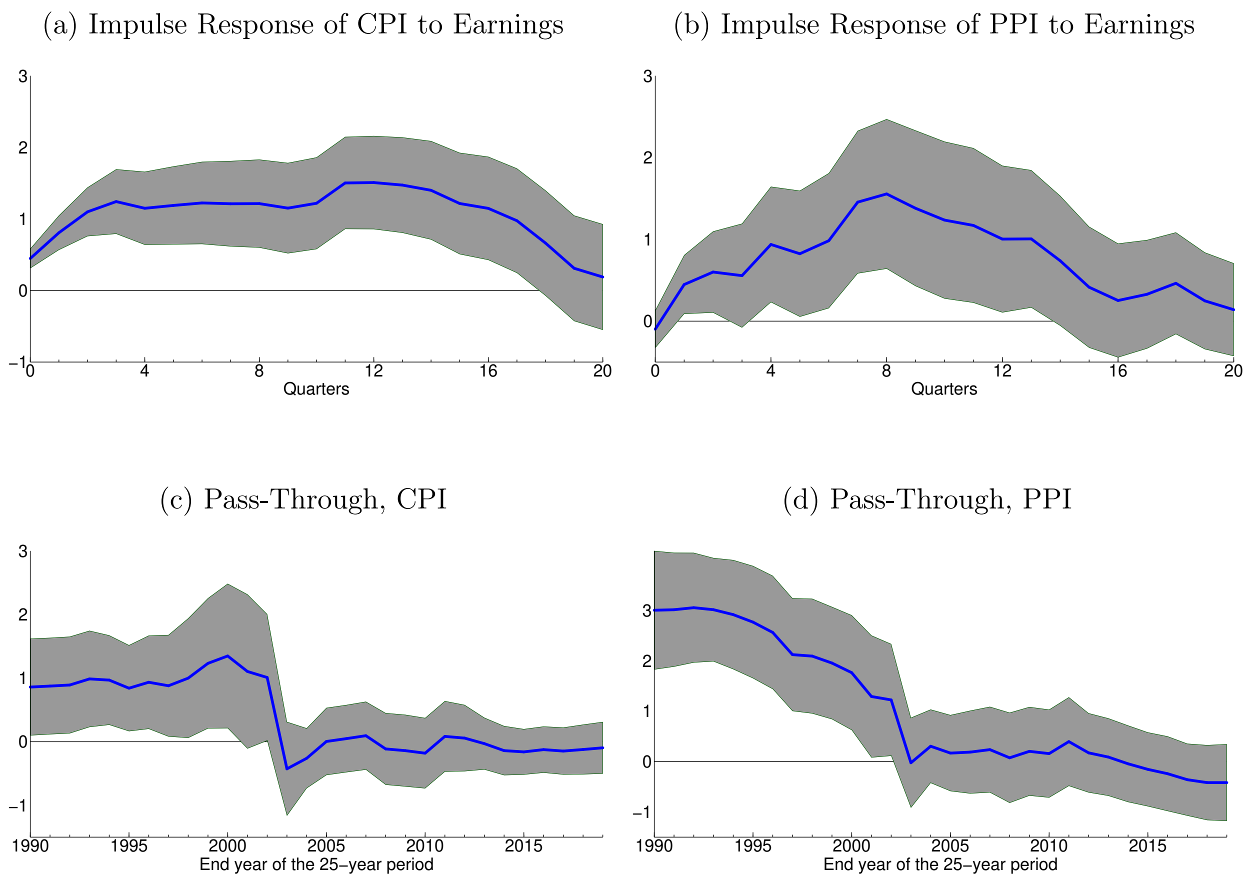
Source: BLS and authors' calculations. Note: The figure plots the cumulative wage inflation against cumulative GDP growth, starting at peak unemployment of the previous recession. Wages are defined as average hourly earnings of production and non-supervisory employees, seasonally adjusted, in the goods-producing industries and service-providing industries, respectively.

Figure A.5: Wage Growth from Four Previous Recessions



Source: BLS and authors' calculations. Note: The figure plots the cumulative wage inflation against time, starting at peak unemployment of the previous recession. Wages are defined as average hourly earnings of production and non-supervisory employees, seasonally adjusted, in the goods-producing industries and service-providing industries, respectively.

Figure A.6: Aggregate Pass-Through Excluding Unemployment Gap



Source: BLS and authors' calculations. Note: The top two panels present the estimated coefficients β_h and their 90 percent confidence intervals from specification (2) run at quarterly frequency, for horizons $h = 0, ..., 20$ quarters. We exclude the unemployment gap variables from this specification. In the top left panel, price inflation is core CPI inflation (All items less food and energy, seasonally adjusted) and wage inflation is average hourly earnings of production and non-supervisory employees. All variables are transformed into a quarterly series by taking a simple average across the months in each quarter. In the top right panel, price inflation is the producer price index (PPI) of finished goods less food and energy. The bottom two panels estimate specification (2) over 25-year rolling windows for $h = 12$ for the CPI and $h = 8$ for the PPI, where the ending year of the 25-year period is indicated on the x-axis.

B Theory

B.1 Detailed Derivations

B.1.1 Cost Function

The firm's production function is

$$y = Al^{\alpha}k^{1-\alpha}. \tag{23}$$

The firm's cost function is

$$C(y) = \min_{\{l,k\}} \{w(i)l + kr\}, \tag{24}$$

where $w(i)$ and r are the cost of labor and capital, respectively, taken as given by the firm, and $w(i) = w_D$ for domestic firms and $w(i) = w_F$ for foreign firms. Minimization of the cost function (24) subject to the production function (23) implies

$$\frac{w(i)}{r} = \frac{\alpha}{1-\alpha}\frac{r}{w(i)}k. \tag{25}$$

The firm's cost function can thus be re-written, using the optimized quantities and plugging in for l, as

$$C(y) = \frac{1}{1-\alpha}rk. \tag{26}$$

From the production function (23), we can substitute for l and then solve for k as a function of output y. This yields

$$k = \frac{1}{A}\left(\frac{\alpha}{1-\alpha}\right)^{-\alpha} r^{-\alpha}w(i)^{\alpha}y. \tag{27}$$

Thus, the cost function is

$$C(y) = \left(\frac{1}{1-\alpha}\right)\left(\frac{\alpha}{1-\alpha}\right)^{-\alpha}\frac{1}{A}r^{1-\alpha}w(i)^{\alpha}y. \tag{28}$$

Marginal costs are therefore

$$c(y) = \left(\frac{1}{1-\alpha}\right)\left(\frac{\alpha}{1-\alpha}\right)^{-\alpha}\frac{1}{A}r^{1-\alpha}w^{\alpha}, \tag{29}$$

as claimed in the main text, where we omit the constant.

B.1.2 Market Structure and Demand Elasticity

Since there is only a finite number of firms, each firm takes into account the e□ect of its price setting on the price index $p(k)$. We can define the e□ective elasticity of demand for a firm as

$$\mathcal{E}(k,i) \equiv -\frac{d\log y(k,i)}{d\log p(k,i)} = \eta - (\eta - \sigma)\frac{\partial \log p(k)}{\partial \log p(k,i)}. \tag{30}$$

From the definition of an industry's price index $p(k) = (\sum_i p(k,i)^{1-\eta})^{1/(1-\eta)}$, we have that

$$\frac{\partial \log p_(k)}{\partial \log p(k,i)} = \frac{p(k,i)^{1-\eta}}{\sum_i p(k,i)^{1-\eta}}, \tag{31}$$

We now define firms' market share as

$$\varphi(k,i) = \frac{p(k,i)y(k,i)}{\sum_{i'} p(k,i')y(k,i')} = \frac{p(k,i)^{1-\eta}}{\sum_{i'} p(k,i')^{1-\eta}} = \frac{p(k,i)^{1-\eta}}{p(k)^{1-\eta}}. \tag{32}$$

Using this expression, we can re-express the demand elasticity (30) as

$$\mathcal{E}(k,i) = \eta - (\eta - \sigma)\varphi(k,i) = \eta(1 - \varphi(k,i)) + \sigma\varphi(k,i). \tag{33}$$

Thus, the firm's demand elasticity is a weighted average of the within-industry and across-industry elasticities of substitution.

B.1.3 Price Setting

The firm's profit maximization problem

$$\max_p \, [p - c(k,i)] \left(\frac{p}{p(k)}\right)^{-\eta} \left(\frac{p(k)}{P}\right)^{-\sigma} Y \tag{34}$$

leads to the first-order condition

$$\begin{aligned} &\left[(1-\eta)p(k,i)^{-\eta} + \eta p(k,i)^{-\eta-1}c(k,i)\right] p(k)^{\eta-\sigma}P^{\sigma}Y \\ &+ \left[(\eta-\sigma)p(k,i)^{-\eta}p(k)^{\eta-\sigma-1}P^{\sigma}Y\frac{dp(k)}{dp(k,i)}\right][p(k,i) - c(k,i)] = 0, \end{aligned} \tag{35}$$

where $p(k,i)$ is the profit maximizing price. Substituting in the derivative of the price index,

$$\frac{dp(k)}{dp(k,i)} = \left(\frac{p(k)}{p(k,i)}\right)^{\eta} \tag{36}$$

and using the definition of the market share $\varphi(k,i) = (p(k,i)/p(k))^{1-\eta}$ yields

$$p(k,i) = \frac{\eta - (\eta-\sigma)\varphi(k,i)}{(\eta-1) - (\eta-\sigma)\varphi(k,i)} c(k,i). \tag{37}$$

Using the definition of the demand elasticity (30), this equation becomes

$$p(k,i) = \frac{\mathcal{E}(k,i)}{\mathcal{E}(k,i)-1} c(k,i) = \mathcal{M}(k,i)c(k,i), \tag{38}$$

where $\mathcal{M}(k,i)$ denotes the firm's markup.

B.1.4 Pass-Through

From equation (38), we can derive the pass-through of shocks into prices as

$$\begin{aligned} d\log p(k,i) &= d\log \mathcal{M}(k,i) + d\log c(k,i) \\ &= d\log \mathcal{M}(k,i) - d\log A + \alpha d\log w(i) + (1-\alpha) d\log r. \end{aligned} \tag{39}$$

The change in the markup is given by

$$\begin{aligned} d\log \mathcal{M}(k,i) &= d\log\left[\eta - (\eta-\sigma)\varphi(k,i)\right] - d\log\left[(\eta-1) - (\eta-\sigma)\varphi(k,i)\right] \\ &= \left[-\frac{\eta-\sigma}{\eta-(\eta-\sigma)\varphi(k,i)} + \frac{\eta-\sigma}{(\eta-1)-(\eta-\sigma)\varphi(k,i)}\right] \frac{\partial\varphi(k,i)}{\partial\log\varphi(k,i)} d\log\varphi(k,i) \\ &= \frac{(\eta-\sigma)\varphi(k,i)}{\left[\eta-(\eta-\sigma)\varphi(k,i)\right]\left[(\eta-1)-(\eta-\sigma)\varphi(k,i)\right]} \left[(1-\eta)d\log p(k,i) - (1-\eta)d\log p(k)\right] \\ &= \frac{\varphi(k,i)}{\left[\frac{\eta}{\eta-\sigma} - \varphi(k,i)\right]\left[1 - \frac{\eta-\sigma}{\eta-1}\varphi(k,i)\right]} \left[d\log p(k) - d\log p(k,i)\right] \\ &= -\Gamma(k,i)\left[d\log p(k,i) - d\log p(k)\right], \end{aligned} \tag{40}$$

where $\Gamma(k,i) = -(\partial\log\mathcal{M}(k,i)/\partial\log p(k,i)) \geq 0$ is the elasticity of the markup with respect to a firm's own price. From

$$\Gamma(k,i) = \frac{\varphi(k,i)}{\left[\frac{\eta}{\eta-\sigma} - \varphi(k,i)\right]\left[1 - \frac{\eta-\sigma}{\eta-1}\varphi(k,i)\right]}, \tag{41}$$

it follows that $\Gamma(k,i) = 0$ if $\varphi(k,i) = 0$.

A firm's pass-through is then given by

$$d\log p(k,i) = -\Gamma(k,i)\left[d\log p(k,i) - d\log p(k)\right] - d\log A + \alpha d\log w(i) + (1-\alpha)d\log r. \quad (42)$$

Solving this equation for $d\log p(k,i)$ and using $d\log r = 0$, we find

$$d\log p(k,i) = \frac{\Gamma(k,i)}{1+\Gamma(k,i)}d\log p(k) - \frac{1}{1+\Gamma(k,i)}d\log A + \frac{\alpha}{1+\Gamma_s(k,i)}d\log w(i), \quad (43)$$

which is our main pass-through equation, equation (15).

Finally, the derivative of the markup elasticity with respect to the market share $\varphi(k,i)$ is given by

$$\frac{d\Gamma(k,i)}{d\varphi(k,i)} = \frac{\left[\frac{\eta}{\eta-\sigma} - \varphi(k,i)\right]\left[1 - \frac{\eta-\sigma}{\eta-1}\varphi(k,i)\right] + \left[1 - \frac{\eta-\sigma}{\eta-1}\varphi(k,i)\right] + \frac{\eta-\sigma}{\eta-1}\left[\frac{\eta}{\eta-\sigma} - \varphi(k,i)\right]}{\left\{\left[\frac{\eta}{\eta-\sigma} - \varphi(k,i)\right]\left[1 - \frac{\eta-\sigma}{\eta-1}\varphi(k,i)\right]\right\}^2} > 0. \quad (44)$$

B.2 Proof of Theorem

From the pass-through equation (15), domestic firm d's price change in response to a change in the domestic wage w_d, holding productivity fixed, is given by

$$d\log p(k,d) = \frac{\alpha}{1+\Gamma(k,d)}d\log w_d + \frac{\Gamma(k,d)}{1+\Gamma(k,d)}d\log p(k). \quad (45)$$

Since the price index is a□ected by the change in each firm's price, we have

$$\frac{d\log p(k,d)}{d\log w_d} = \frac{\alpha}{1+\Gamma(k,d)} + \frac{\Gamma(k,d)}{1+\Gamma(k,d)}\sum_{j\in N(k)}\left[\frac{\partial \log p(k)}{\partial \log p(k,j)}\frac{d\log p(k,j)}{d\log w_d}\right]. \quad (46)$$

From the definition of an industry's price index $p(k) = (\sum_i p(k,i)^{1-\eta})^{1/(1-\eta)}$, we have that

$$\frac{\partial \log p(k)}{\partial \log p(k,i)} = \frac{p(k,i)^{1-\eta}}{\sum_i p(k,i)^{1-\eta}} = \varphi(k,i). \quad (47)$$

Therefore,

$$\frac{d\log p(k,d)}{d\log w_d} = \frac{\alpha}{1+\Gamma(k,d)} + \frac{\Gamma(k,d)}{1+\Gamma(k,d)}\sum_{j\in N(k)}\left[\varphi(k,j)\frac{d\log p(k,j)}{d\log w_d}\right]. \quad (48)$$

In other words, pass-through of a wage shock is a combination of the direct effect and a combination of all other firms' price adjustments to the shock, weighted by each firm's market share.

Since all firms have symmetric market shares, we can combine the responses of all domestic and all foreign firms to obtain

$$\frac{d\log p(k,d)}{d\log w_d} = \frac{\alpha}{1+\Gamma(k,d)} + \frac{\Gamma(k,d)}{1+\Gamma(k,d)}\varphi_D(k)\frac{d\log p(k,d)}{d\log w_d} + \frac{\Gamma(k,d)}{1+\Gamma(k,d)}\varphi_F(k)\frac{d\log p(k,f)}{d\log w_d}, \tag{49}$$

where $\varphi_D(k) = \sum_{j\in D}\varphi(k,j)$ is the total market share of domestic firms and $\varphi_F(k) = \sum_{j\in F}\varphi(k,j)$ is the total market share of foreign firms. Re-arranging yields

$$\frac{d\log p(k,d)}{d\log w_d} = \frac{\alpha + \Gamma(k,d)\varphi_F(k)\frac{d\log p(k,f)}{d\log w_d}}{1+\Gamma(k,d)(1-\varphi_D(k))}. \tag{50}$$

We obtain the pass-through of foreign firms through similar steps, noting that they are only affected by the change in the price index $p(k)$ since their wage is unchanged,

$$\frac{d\log p(k,f)}{d\log w_d} = \frac{\Gamma(k,f)\varphi_D(k)\frac{d\log p(k,d)}{d\log w_d}}{1+\Gamma(k,f)(1-\varphi_F(k))}. \tag{51}$$

Combining the pass-through of domestic and foreign firms yields

$$\frac{d\log p(k,d)}{d\log w_d} = \frac{\alpha\left[1+\Gamma(k,f)\varphi_D(k)\right]}{1+\Gamma(k,d)(1-\varphi_D(k))+\Gamma(k,f)\varphi_D(k)}, \tag{52}$$

where $\Gamma(k,d) = \Gamma(k,f)$ since all firms have the same market share. We will now use this equation to prove the two parts of the theorem.

<u>Proof of Part 1:</u> By definition of the markup elasticity, for every firm i,

$$\Gamma(k,i) = \frac{\varphi(k,i)}{\left[\frac{\eta}{\eta-\sigma}-\varphi(k,i)\right]\left[1-\frac{\eta-\sigma}{\eta-1}\varphi(k,i)\right]} > 0, \tag{53}$$

and, from equation (44), $d\Gamma(k,i)/d\varphi(k,i) > 0$. A decline in $D(k)$ for a given $\varphi_D(k)$ implies that each remaining domestic firm has higher market share, hence $\Gamma(k,d)$ increases. Differentiating equation (52) with respect to the domestic markup elasticity yields

$$\frac{\partial\frac{d\log p(k,f)}{d\log w_d}}{\partial\Gamma(k,d)} = -\frac{\alpha(1-\varphi_D(k))\left[1+\Gamma(k,f)\varphi_D(k)\right]}{\left[1+\Gamma(k,d)(1-\varphi_D(k))+\Gamma(k,f)\varphi_D(k)\right]^2} < 0, \tag{54}$$

hence pass-through of domestic firms declines.

Proof of Part 2: Since the market share of each individual firm remains unchanged, $\Gamma(k,d)$ and $\Gamma(k,f)$ remain unchanged. The substitution of a foreign firm for a domestic firm reduces the overall market share of domestic firms, $\varphi_D(k)$, at the expense of foreign firms. Differentiating equation (52) with respect to the domestic market share yields

$$\frac{\partial \frac{d \log p(k,f)}{d \log w_d}}{\partial \varphi_D(k)} = \frac{\alpha \Gamma(k,d)\left[1+\Gamma(k,f)\right]}{\left[1+\Gamma(k,d)(1-\varphi_D(k))+\Gamma(k,f)\varphi_D(k)\right]^2} > 0. \tag{55}$$

Hence, a decline in the domestic market share reduces pass-through.

C Pass-through Estimates: Local Projections

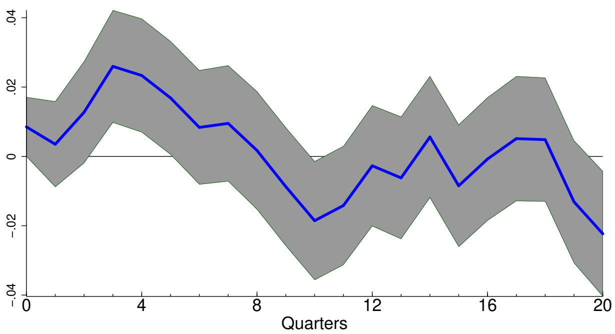
We estimate impulse response functions similar to specification (2) for each quarter $h = 0, ..., 20$

$$\Delta \ln(p_{i,t+h}) = \beta_h \Delta \ln(w_{it}) + \sum_{j=1}^{8} \delta_j \Delta \ln(p_{i,t-j}) + \sum_{j=1}^{8} \zeta_j \Delta \ln(w_{i,t-j}) + \eta X_{it} + \xi_i + \rho_t + \epsilon_{it}, \quad (56)$$

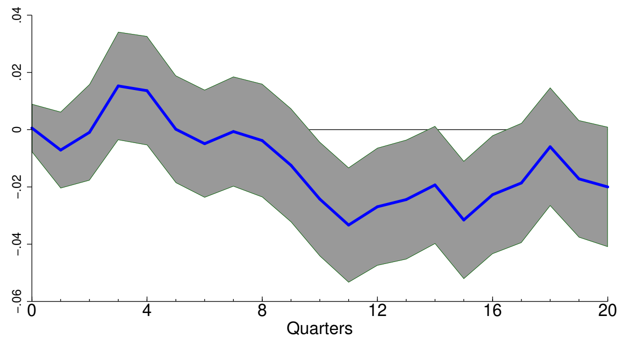
where p_{it} is the producer price index in industry i and period t and $\Delta p_{i,t+h}$ is its four-quarter change between quarter $t+h-4$ and $t+h$. Similarly, Δw_{it} is the four-quarter change in the industry's wage index between $t-4$ and t and X_{it} is a set of time-varying controls that include the four-quarter change of the industry's TFP. We also control for the changing age and gender composition of an industry's workforce with X_{it} to control for compositional changes in an industry's workforce. These controls are the same as in the main text. While we do not observe industry-specific capital costs, we control for fixed differences across industries by including industry fixed effects ξ_i, and we control for macroeconomic trends by adding time fixed effects ρ_t. These time fixed effects also pick up variation in the aggregate unemployment gap, which is therefore not included separately. The coefficient β_h captures the pass-through of wage changes to price changes h quarters ahead.

The top left panel of Figure C.1 shows the estimated coefficients β_h a horizons 1 to 20 quarters using all industries in our dataset for the period 2003 to 2017. Pass-through of wage shocks increases over the first quarters until its peak in quarter 3 at about 0.03, and then declines again and becomes insignificant in quarter 6. However, the result masks considerable heterogeneity across goods and services. The right panel of Figure C.1 presents the impulse response function for manufacturing industries only. Pass-through is statistically insignificant at most horizons, and is in fact negative from quarter 10 onwards. In contrast, the bottom panel of Figure C.1 shows that pass-through in services is significantly positive for 9 quarters, with an average value of about 0.04. Thus, the positive relationship between wage changes and price changes found in the aggregate appears to be entirely due to the pass-through in service-producing industries.

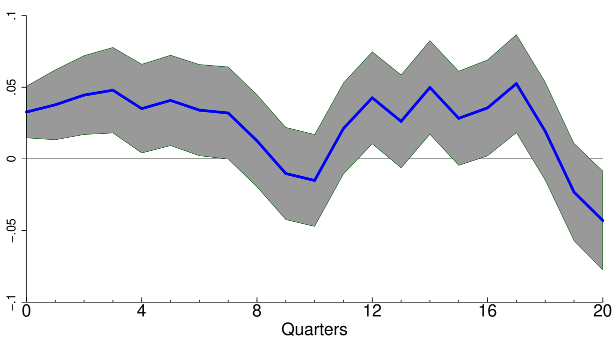
Figure C.1: Impulse Response Functions



(a) Manufacturing and Services



(b) Manufacturing



(c) Services

Source: BLS, Census Bureau Quarterly Census of Employment and Wages, authors' calculations. Note: The figure presents the estimated coefficients β_h from specification (56) and their 90 percent confidence intervals for price inflation at $h = 1, ..., 20$ quarters. Prices are the seasonally-adjusted producer price indices and wages are the seasonally-adjusted average weekly wages of 5-digit NAICS industries. All data are at the quarterly frequency. Controls in the regression are TFP, employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Panel (a) presents the estimated coefficients β_h based on a regression using all industries in our sample. Panels (b) and (c) are constructed by running specification (16) only for manufacturing industries and only for services industries, respectively.

D Data Appendix

In this section, we describe the data sources and the variables used for our industry-level regressions. All variables are aggregated to the quarterly frequency.

Prices ($\Delta_{t-h,t} \ln(p_{it})$). We obtain monthly industry-level price data from the Producer Price Index (PPI) of the Bureau of Labor Statistics (BLS). The PPI collects the average monthly selling prices for domestically produced goods and services at various levels of industry disaggregation. Indices for most manufacturing industries go back to the 1990s, while comprehensive coverage for most service industries does not begin until 2003. The PPI accounts for the near universe of output in the goods-producing sector and approximately three-quarters of the output in the service-providing sector.

We download all available 5-digit NAICS industry PPI series from the BLS website. Since some 5-digit NAICS codes change over time or are aggregated differently, we construct time-consistent NAICS codes using the list of NAICS revisions from 1997 to 2017 provided by the U.S. Census Bureau. We splice together NAICS codes that based on the Census description refer to the same industry when industry codes change over time. Moreover, we combine disaggregated 6-digit NAICS codes into one if a given 5-digit code can be extended forward or backward from these more disaggregated codes. This aggregation is performed by taking a weighted average over the changes in the 6-digit PPI series involved, using total shipments from the Economic Census in 2002 as weights.

We fill in missing observations using linear interpolation if data are missing for fewer than three consecutive months. We treat observations as missing when data for an industry are missing for three or more consecutive months. We remove seasonality from the PPI series using the Census' X-12-ARIMA Seasonal Adjustment program, and aggregate the price indices to the quarterly frequency by taking the three-month averages.

We exclude mining, agriculture, and utilities from all analyses since prices in the former two are driven mostly by commodity prices while in the latter prices are subject to regulation. We also exclude NAICS starting with 324, Petroleum and Coal Products Manufacturing, and NAICS 33111, Iron and Steel Mills and Ferroalloy Manufacturing, since these series fluctuate significantly based on the commodity price.

Our final dataset contains quarterly price data for 255 time-consistent 5-digit NAICS industries. For most manufacturing industries, the data start in 1993. For most services industries, the data are available from 2003. We transform all prices into log prices and compute log price changes between quarter t and quarter $t-h$, where $t = 1, ..., 20$. For each h, we drop observations with price changes below the 1st and above the 99th percentile of the price change distribution.

Wages ($\Delta_{t-h,t}\ln(w_{it})$). We obtain average weekly earnings in each quarter at the 5-digit NAICS industry level from the Quarterly Census of Employment and Wages (QCEW) from the BLS. The QCEW reports for each quarter and industry the number of establishments, employment, and the weekly average wage for workers covered by State unemployment insurance (UI) laws and Federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program. Overall, the data cover more than 95 percent of U.S. jobs. The QCEW data are collected by state agencies and reported to the BLS, and represent the total compensation paid during the calendar quarter, including bonuses, stock options, severance pay, and so on for most states. For most industries, the data cover the period from 1990 to 2018. We create time-consistent 5-digit NAICS codes using the same mapping as before and seasonally adjust the data.

Our final dataset contains quarterly wage data for 255 time-consistent 5-digit NAICS industries, which we merge with the price data. We transform all wages into log wages and compute log wage changes between quarter t and quarter $t-h$, where $t=1,...,20$.

TFP ($\Delta_{t-h,t}\ln(A_{it})$). We obtain annual estimates of multifactor productivity (MFP) from the BLS.

For the manufacturing sector, the BLS provides estimates at the 4-digit NAICS level, and at greater disaggregation for some industries. The data are available for the 1987-2016 period. Whenever MFP is missing for an industry at a given aggregation level, we use the finest higher level of aggregation available. For example, MFP is not available for NAICS 31499. We therefore assign the MFP of NAICS 3149 to that industry. We transform the annual MFP data into a quarterly series by assigning the same MFP to all quarters of a given year.

For non-manufacturing industries, the BLS does not provide productivity estimates with the same level of granularity as for manufacturing. We therefore use annual MFP estimates at the two or three digit NAICS level from the Integrated Industry-Level Production Account (KLEMS) tables provided by the BLS. We use for each industry the productivity value at the next available higher level of aggregation. As in manufacturing, we transform the annual MFP data into a quarterly series by assigning the same MFP to all quarters of a given year.

Since the productivity data end in 2016, our final dataset for both goods and services spans the period from 2003-2016, and for the manufacturing sector alone from 1993-2016.

Additional Controls (X_{it}). We obtain quarterly employment by gender, education, and age from the Quarterly Workforce Indicators (QWI) at the four digit NAICS level from 1990 to 2018. For each 4-digit industry and quarter, we compute the share of male and female workers. Similarly, we compute the share of high-skilled workers, defined by those who have a bachelor's degree or higher, the share of workers who have at most an associate's degree, and the share of workers who have at most a high school or equivalent degree (no college). We generate the shares of young, middle-aged, and older workers by defining young workers as those aged below 24 years, middle-aged as those 25-54, and older as those 55 and older. We merge the information into our dataset, using for each 5-digit industry the information of the corresponding higher-level 4-digit industry. For example, for NAICS 31499, we use the age, gender, and education shares of the 4-digit NAICS 3149. The final data thus contains quarterly age, gender, and education shares for each 5-digit NAICS.

Labor Share (α_{it}). We obtain each 5-digit industry's total payroll and total value of shipments in census years (2002, 2007, 2012) from the Census of Manufacturing and in all other years between 1997 and 2016 from the Annual Survey of Manufacturers (ASM). We then compute each industry's labor share as its total payroll divided by the total value of shipments. We apply the labor share of 1997 to the years prior to 1997. We also compute an alternative labor share as total payroll divided by value added for the manufacturing sector. We transform the annual data into a quarterly series by assigning the same labor share to all quarters of a given year.

For the non-manufacturing sector, we use the Economic Census to obtain each 5-digit industry's total payroll and sales in 2002, 2007, and 2012. We then construct the labor share as payroll divided by sales. For non-manufacturing, no value added information is available and hence we cannot construct a value-added based labor share as in manufacturing. We assume that the labor share remains constant in between census years until a new release becomes available, and apply the labor share of 2012 to the years after 2012. We transform the annual data into a quarterly series.

Import Penetration ($\Delta_{1997,t}IP_{it}$). We obtain imports and exports for each 5-digit NAICS industry in manufacturing in each year between 1993 and 2016 from the U.S. Census Bureau, available from Peter Schott's website (https://sompks4.github.io/sub_data.html). We download each industry's total value of shipments in census years (2002, 2007, and 2012) from the Census of Manufacturing and in non-census years between 1997 and 2016 from the Annual Survey of Manufacturers (ASM). We apply the shipments of 1997 to the period 1993 to 1996. We then construct the change in import penetration in each year for each industry according to equation (19), and transform the annual data into a quarterly series by applying the annual values to all quarters of the same year.

Concentration (C_{it}). We download the market share of the top-4 and top-20 firms as well as the Herfindahl-Hirschmann Index (HHI) for each 5-digit NAICS industry in manufacturing from the Census of Manufacturing in 1997, 2002, 2007, 2012, and 2017. We then construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2017. We transform the annual data into a quarterly series by applying the annual values to all quarters of the same year.

E Pass-through Estimates: Multiplier Approach

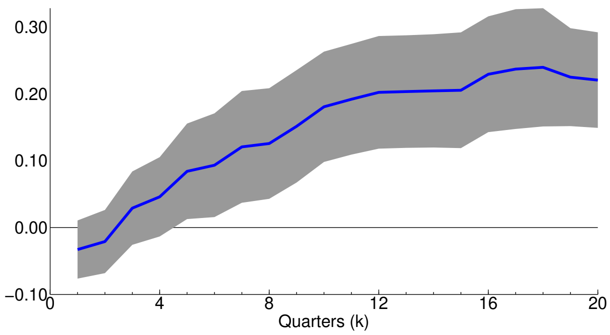
We construct the impulse response function of a change in wages on prices using an instrumental variables local projection (IV-LP) (e.g., Ramey (2016)). In our context, a wage shock can induce a dynamic path of wages, generating serial correlation, which could confound our estimates of the pass-through of a wage shock to prices. We therefore construct wage shock multipliers by estimating, for $k = 1, ..., 20$, regressions of the form

$$\sum_{j=1}^{k} (\ln(p_{i,t+j}) - \ln(p_{it})) = \beta_k \sum_{j=1}^{k} (\ln(w_{i,t+j}) - \ln(w_{it})) + \gamma X_{it} + \delta_i + \rho_t + \epsilon_{it}, \tag{57}$$

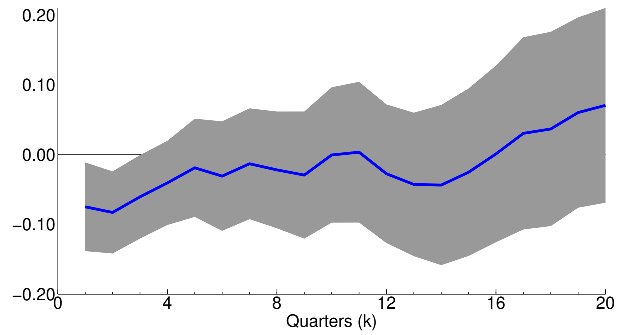
where p_{it} is the producer price index in industry i and quarter t and w_{it} is the industry's wage index. We instrument for the cumulative wage term $\sum_{j=1}^{k}(\ln(w_{i,t+j}) - \ln(w_{it}))$ with the contemporaneous change in wages, $\ln(w_{it}) - \ln(w_{i,t-4})$ to obtain the impact of a contemporaneous wage shock. The controls X_{it} include the log change in industry i's TFP between quarter t and $t + k$, as well as the same controls as in the main text for the composition of the industry's workforce in quarter t. We control for fixed differences across industries by including industry fixed effects δ_i, and we control for macroeconomic trends by adding time fixed effects ρ_t. These time fixed effects also pick up variation in the aggregate unemployment gap, which is therefore not included separately. The coefficient β_k captures the total impact of a change in wages on prices between t and $t + k$ induced by a contemporaneous wage shock. We estimate the equation via two-stage least squares. We weight the regression by an industry's total sales in 2012, and use Driscoll-Kraay standard errors with bandwidth two quarters to account for cross-sectional and time series correlation.

The top left panel of Figure E.1 shows the estimated IV coefficients β_k for $k = 1, ..., 20$ using all industries in our dataset for the period 2003 to 2016. Pass-through of wage shocks increases steadily over time, peaking at about 24% after 18 quarters. However, the result masks considerable heterogeneity across goods and services. The right panel of Figure E.1 presents results for manufacturing industries only. Pass-through is statistically insignificant at most horizons, and is in fact negative for the first three quarters. In contrast, the bottom left panel of Figure E.1 shows that pass-through in services is significant and positive at most horizons, reaching 37% at 16 quarters. Thus, the positive relationship between wage changes and price changes found in the aggregate appears to be driven by pass-through in service-producing industries.

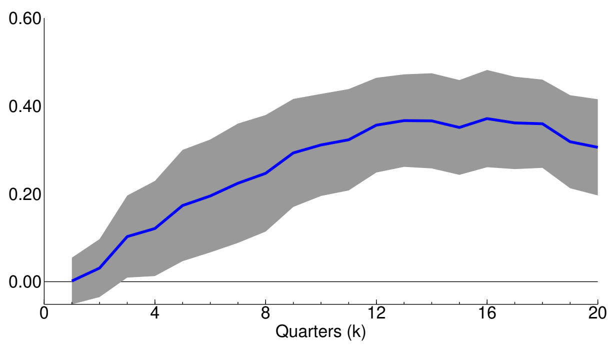
Figure E.1: Impulse Response Functions using the IV-LP Approach



(a) All Industries



(b) Manufacturing



(c) Services

Source: BLS, Census Bureau Quarterly Census of Employment and Wages, authors' calculations. Note: The figure presents the estimated coefficients β_k from specification (57) and their 90 percent confidence intervals for $k = 1, ..., 20$ quarters. Prices are the seasonally-adjusted producer price indices and wages are the seasonally-adjusted average weekly wages of 5-digit NAICS industries. All data are at the quarterly frequency. Controls in the regression are the log change in TFP between t and $t + k$, employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Panel (a) presents the estimated coefficients β_k based on a regression using all industries in our sample. Panels (b) uses only manufacturing industries and Panel (c) uses only service industries.

F Additional Tables on Industry-Level Pass-Through

In this section we present additional pass-through specifications to show that the results in the main text are robust to different lag lengths and an alternative definition of the labor share.

Table F.1 shows the regression results for specification (16) using a lag length of $h = 4$ quarters, and Table F.2 uses a lag length of $h = 12$ quarters. The results are similar to the main text.

Table F.3 presents regressions that are not weighted by each industry's sales share in 2012, at lag length $h = 8$. The results are qualitatively similar to the main text, although the point estimates on pass-through are smaller in absolute value than in the weighted regressions. Table F.4 runs the regressions with different fixed effect configurations. Pass-through in services remains strongly positive, and small or negative in manufacturing.

Tables F.5 and F.6 show the regression results for the estimation using only the manufacturing sector, specification (18), using $h = 4$ quarters and $h = 12$ quarters, respectively. We still find a significant decline in pass-through in manufacturing.

Table F.7 presents our regression results for the manufacturing sector using an alternative definition of the labor share, where we now define it as payroll divided by value added. The estimated coefficients are very similar to the results obtained using the labor share as a fraction of total sales.

Table F.1: Pass-Through Regressions for Goods versus Services ($h = 4$)

	No Labor Share			Labor Share		
Δ PPI	(1) Aggregate	(2) No TFP	(3) With TFP	(4) Aggregate	(5) No TFP	(6) With TFP
ΔWage	0.0478***					
	(0.0175)					
ΔTFP	-0.0787***		-0.0735***	-0.0782***		-0.0757***
	(0.0163)		(0.0144)	(0.0171)		(0.0165)
ΔWage Manuf		-0.0217	-0.0110			
		(0.0178)	(0.0179)			
ΔWage Services		0.101***	0.0913***			
		(0.0373)	(0.0325)			
ΔWage $\times$ LS				0.164**		
				(0.0804)		
ΔWage Manuf $\times$ LS					-0.242**	-0.123
					(0.111)	(0.104)
ΔWage Services $\times$ LS					0.241**	0.196**
					(0.113)	(0.0919)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0175	0.0125	0.0203	0.0169	0.00921	0.0174
Observations	12683	12683	12683	12683	12683	12683

Note: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (16), where the changes in wages, in TFP, and in the PPI are computed over a 4-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results. Columns 2 and 3 present the regression where we interact the change in wages with a dummy for the manufacturing sector and a dummy for the services sector, respectively. We exclude the change in TFP in column 2 and include it in column 3. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. These regressions also include a control for the labor share in levels, omitted from the table for simplicity. R-squared is the Within R-squared excluding fixed effects.

Table F.2: Pass-Through Regressions for Manufacturing versus Services ($h = 12$)

	No Labor Share			Labor Share		
Δ PPI	(1) Aggregate	(2) No TFP	(3) With TFP	(4) Aggregate	(5) No TFP	(6) With TFP
ΔWage	0.131***					
	(0.0273)					
ΔTFP	-0.107***		-0.0926***	-0.0985***		-0.0944***
	(0.0263)		(0.0260)	(0.0245)		(0.0243)
ΔWage Manuf		-0.0425	-0.0245			
		(0.0258)	(0.0274)			
ΔWage Services		0.234***	0.220***			
		(0.0373)	(0.0357)			
ΔWage $\times$ LS				0.660***		
				(0.121)		
ΔWage Manuf $\times$ LS					-0.0859	0.0324
					(0.174)	(0.183)
ΔWage Services $\times$ LS					0.770***	0.727***
					(0.144)	(0.131)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0509	0.0531	0.0630	0.0550	0.0468	0.0569
Observations	11324	11324	11324	11324	11324	11324

Note: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (16), where the changes in wages, in TFP, and in the PPI are computed over a 12-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results. Columns 2 and 3 present the regression where we interact the change in wages with a dummy for the manufacturing sector and a dummy for the services sector, respectively. We exclude the change in TFP in column 2 and include it in column 3. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. These regressions also include a control for the labor share in levels, omitted from the table for simplicity. R-squared is the Within R-squared excluding fixed effects.

Table F.3: Pass-Through Regressions for Manufacturing versus Services, Unweighted Regressions ($h = 8$)

	No Labor Share			Labor Share		
Δ PPI	(1) Aggregate	(2) No TFP	(3) With TFP	(4) Aggregate	(5) No TFP	(6) With TFP
ΔWage	0.0597***					
	(0.0154)					
ΔTFP	-0.0735***		-0.0647***	-0.0717***		-0.0667***
	(0.0178)		(0.0164)	(0.0175)		(0.0164)
ΔWage Manuf		0.00126	0.00865			
		(0.0123)	(0.0133)			
ΔWage Services		0.165***	0.154***			
		(0.0310)	(0.0289)			
ΔWage × LS				0.285***		
				(0.0919)		
ΔWage Manuf × LS					-0.0627	-0.0131
					(0.0669)	(0.0713)
ΔWage Services × LS					0.498***	0.455***
					(0.130)	(0.118)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0156	0.0159	0.0209	0.0164	0.0130	0.0185
Observations	12271	12271	12271	12058	12058	12058

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to the labor share. Driscoll-Kraay standard errors with a bandwidth of 2 quarters shown in parenthesis. Labor share composition controls in the regression are employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. R-squared is the Within R-squared excluding fixed effects. The table shows the results from running specification (16) without weighting by an industry's total sales in 2012.

Table F.4: Pass-Through Regressions for Manufacturing versus Services with Different Fixed Effects ($h = 8$)

	No Labor Share			Labor Share		
Δ PPI	(1) No Ind FE	(2) No Time FE	(3) No FE	(4) No Ind FE	(5) No Time FE	(6) No FE
ΔWage Manuf	-0.00473	-0.000378	0.0639*			
	(0.0385)	(0.0348)	(0.0364)			
ΔWage Services	0.108**	0.214***	0.167***			
	(0.0491)	(0.0348)	(0.0429)			
ΔTFP	-0.136***	-0.100***	-0.144***	-0.136***	-0.102***	-0.139***
	(0.0309)	(0.0238)	(0.0244)	(0.0296)	(0.0242)	(0.0220)
ΔWage Manuf × LS				-0.350*	0.118	0.219
				(0.199)	(0.237)	(0.209)
ΔWage Services × LS				0.364**	0.658***	0.635***
				(0.181)	(0.148)	(0.172)
Time Fixed Effects	Yes	No	No	Yes	No	No
Industry Fixed Effects	No	Yes	No	No	Yes	No
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0627	0.105	0.0872	0.0667	0.0960	0.0870
Observations	12010	12010	12010	12010	12010	12010

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to the labor share. Driscoll-Kraay standard errors with a bandwidth of 2 quarter shown in parenthesis. All regressions are weighted by an industry's total sales in 2012. Labor share composition controls in the regression are employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. R-squared is the Within R-squared excluding fixed effects. Columns 1 and 4 show the results from running the baseline regression (16) without industry fixed effects. Columns 2 and 5 exclude time fixed effects. Columns 3 and 6 exclude all fixed effects.

Table F.5: Pass-Through Regressions in Manufacturing ($h = 4$)

	No Labor Share		Labor Share	
	(1)	(2)	(3)	(4)
Δ PPI	All	Pre/Post	All	Pre/Post
Δ Wage	-0.00229			
	(0.0139)			
Δ TFP	-0.163***	-0.162***	-0.172***	-0.170***
	(0.0239)	(0.0236)	(0.0244)	(0.0242)
Δ Wage × Pre-2003		0.0326*		
		(0.0176)		
Δ Wage × Post-2003		-0.0318*		
		(0.0177)		
Δ Wage × LS			0.000505	
			(0.113)	
Δ Wage × LS × Pre-2003				0.196
				(0.146)
Δ Wage × LS × Post-2003				-0.223
				(0.164)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
R-squared	0.0378	0.0361	0.0416	0.0401
Observations	12833	12833	12833	12833

Note: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (18), where the changes in wages, in TFP, and in the PPI are computed over a 4-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results without the interaction for the pre- and post-period. Column 2 shows the results with the interaction. Columns 3-4 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. These regressions also include a control for the labor share in levels, omitted from the table for simplicity. R-squared is the Within R-squared excluding fixed effects.

Table F.6: Pass-Through Regressions in Manufacturing ($h = 12$)

	No Labor Share		Labor Share	
Δ PPI	(1) All	(2) Pre/Post	(3) All	(4) Pre/Post
Δ Wage	0.0299 (0.0254)			
Δ TFP	-0.163*** (0.0166)	-0.160*** (0.0164)	-0.190*** (0.0184)	-0.184*** (0.0174)
Δ Wage × Pre-2003		0.150*** (0.0267)		
Δ Wage × Post-2003		-0.0452* (0.0256)		
Δ Wage × LS			0.529*** (0.166)	
Δ Wage × LS × Pre-2003				0.994*** (0.239)
Δ Wage × LS × Post-2003				0.0852 (0.209)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
R-squared	0.0443	0.0466	0.0633	0.0643
Observations	11014	11014	11014	11014

Note: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (18), where the changes in wages, in TFP, and in the PPI are computed over a 12-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results without the interaction for the pre- and post-period. Column 2 shows the results with the interaction. Columns 3-4 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. These regressions also include a control for the labor share in levels, omitted from the table for simplicity. R-squared is the Within R-squared excluding fixed effects.

Table F.7: Pass-Through Regressions with Value-Added for Labor Share ($h = 8$)

Δ PPI	(1) 2003-2016	(2) 1993-2016	(3) Pre/Post	(4) IP	(5) Conc-20	(6) All
Δ Wage × LS	-0.0699	0.0909		0.177**	0.735***	
	(0.112)	(0.0842)		(0.0801)	(0.187)	
Δ TFP	-0.195***	-0.215***	-0.211***	-0.219***	-0.277***	-0.276***
	(0.0298)	(0.0230)	(0.0224)	(0.0231)	(0.0270)	(0.0256)
Δ Wage × LS × Pre-2003			0.202**			1.076***
			(0.0888)			(0.226)
Δ Wage × LS × Post-2003			-0.0342			0.654**
			(0.116)			(0.247)
Δ Wage × LS × Δ IP				-0.580***		-0.323
				(0.165)		(0.229)
Δ Wage × LS × Δ Conc					-0.944***	-1.122***
					(0.268)	(0.304)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0503	0.0567	0.0539	0.0629	0.117	0.120
Observations	7351	11922	11922	11353	8320	7925

Note: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from various specifications, where we define the labor share as payroll divided by value added. The changes in wages, in TFP, and in the PPI are computed over an 8-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the regression results from specification (16) for $h = 8$, which we run only for the manufacturing sector. Column 2 presents the results from the same regression using the extended time period. Column 3 shows the estimated coefficients from specification (18). Column 4 presents the results from specification (20), column 5 the estimates from specification (21), and column 6 the results from (22). These regressions also include a control for the labor share in levels, omitted from the table for simplicity. Additionally, coefficients for ΔIP, $Conc$, and their interactions with the labor share are omitted. R-squared is the Within R-squared excluding fixed effects.

G Using Job-to-Job Transitions to Identify the Effect of Labor Costs on Prices

We build on the insights in Moscarini and Postel-Vinay (2017a) who show using a job ladder model embedded in a New Keynesian framework that inflationary wage growth occurs when it represents competitive pressures in hiring and retention. Such pressure materializes when firms try to poach employees of other firms, which leads the poachers to bid up the wages of employed workers and incumbent firms raising their wages to increase retention. Wage growth due to such a mechanism is inflationary precisely because it raises wages for people without raising their productivity.

To implement this idea and isolate the wage growth due to competition between employers, we build on empirical work in Karahan et al. (2017) and Moscarini and Postel-Vinay (2017b). These papers show that when the frequency of job-to-job transitions increases, wage growth accelerates more than it does in response to improvements in the job-finding rate for the unemployed, consistent with a large class of job ladder models such as Burdett and Mortensen (1998) and Postel-Vinay and Robin (2002). We use the realized job-to-job transitions to instrument for wage growth. In other words, controlling for productivity, the variation in wage growth predicted by job-to-job transitions is the inflationary component of wage growth. The exclusion restriction behind this instrument is that the competition between firms for workers does not affect firms' pricing decisions directly; rather, wages are affected due to competition and prices change only in response to increasing unit labor costs.

We construct the instrument using publicly available, quarterly job-to-job transition rates from the Longitudinal Employer Household-Dynamics (LEHD).[21] The publicly available LEHD data provide job-to-job transition rates at the two-digit sector level, separately by gender and education level, since 2000. Using this information, we impute the job-to-job transition rate for each of the 5-digit industries in our sample as a weighted average over the job-to-job transition rates by gender and education within the associated two-digit sector, using the gender and education shares of workers in our disaggregated industries as weights. The instrument therefore picks up time variation in job-to-job transitions for the aggregate sector level and in the composition of workers in a given industry. There is less variation in manufacturing, since the LEHD treats manufacturing as a single sector ($31-33$). We then estimate the baseline pass-through specification (16) via instrumental variables, separately for goods and for services, where we instrument for the wage change of industry i in sector

[21] We use the job-to-job transition rates calculated using separations.

$\mathcal{S}$ with the first-stage regression

$$\Delta_{t-h,t} w_{it}^{\mathcal{S}} = \beta^{\mathcal{S}} JtoJ_{it}^{\mathcal{S}} + \gamma^{\mathcal{S}} X_{it}^{\mathcal{S}} + \delta_i^{\mathcal{S}} + \rho_t^{\mathcal{S}} + \epsilon_{it}^{\mathcal{S}}, \tag{58}$$

where $JtoJ_{it}^{\mathcal{S}}$ is the moving average of industry i's job-to-job transition rate in quarter t and its three lags for sector $\mathcal{S}$.

The first-stage estimates in column 1 of Table G.1 show that job-to-job transitions are a relatively weak instrument for the change in wages in the services sector (F-stat: 3.29). The IV estimates in column (2) show that pass-through in the services sector is basically one-for-one. For the manufacturing sector, we find that the first-stage is somewhat weaker, but still significant, due to the lack of variation in job-to-job transitions data across industries within manufacturing (column (3)). We find that pass-through in the manufacturing is negative and not precisely estimated due to lack of detailed job-to-job transitions data in manufacturing industries.

Overall, the IV estimates in Table G.1 confirm the conclusions of the reduced-form findings. Cost-push shocks pass through to prices one for one in service-producing industries, whereas there is little or no pass-through in manufacturing.[22]

[22] We also examined a Bartik-style instrument for minimum wages, which we constructed by aggregating state-level data to the industry-level using employment shares. The first-stage regressions were generally insignificant.

Table G.1: IV Regressions ($h = 8$)

Δ PPI	Services (1) Δ Wage	(2) Δ Price	Manufacturing (3) Δ Wage	(4) Δ Price
J2J	1.532*		12.17	
	(0.844)		(8.834)	
Δ TFP	-0.0843**	0.0573	0.0852***	-0.0587
	(0.0375)	(0.115)	(0.0174)	(0.119)
Δ Wage Services		1.672**		
		(0.825)		
Δ Wage Manuf				-1.406
				(1.296)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
Observations	4659	4659	7332	7332
F-Statistic	3.294		1.90	

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. Driscoll-Kraay standard errors with a bandwidth of 2 quarters shown in parenthesis. All regressions are weighted by an industry's total sales in 2012. Controls in the regression are employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers.

H Further Results on Import Penetration and Competition

In this section, we provide some additional analyses on the eﬀect of import competition and concentration on wage-price pass-through.

Tables H.1 and H.2 re-run the specification involving import penetration (20) computing changes using $h = 4$ and $h = 12$ quarters, respectively. We still find that higher import penetration is associated with lower pass-through, although we lose significance at $h = 4$ when we do not interact with the labor share. Table H.3 re-runs the same specification but instead of using the change in overall import penetration uses only the change in import penetration from China. While again we lose significance if we do not control for the labor share, the eﬀect of import penetration on pass-through is negative and strongly significant once we take the labor share into account.

Figure H.1 shows the evolution of the top-4 market share and the HHI in manufacturing over time. Both measures have significantly increased since the 1990s, although there was a decline in the recent period.

Tables H.4 and H.5 re-run the specification for sales concentration (21) computing changes using $h = 4$ and $h = 12$ quarters, respectively. We still find that higher market concentration is strongly associated with lower wage-price pass-through.

Table H.6 runs specification (21) but instead of sales concentration uses employment concentration, which we obtain from Walls & Associates' National Establishment Time-Series (NETS) database for 1993-2014. We compute the share of employees working for the top-4 and top-20 employers, respectively, in our data in each year, and similarly compute an employment HHI. The results are similar to before.

Tables H.7 and H.8 re-run the specification combining import penetration and concentration (22) computing changes using $h = 4$ and $h = 12$ quarters, respectively. The conclusions are very similar as in the main text. Concentration explains a larger part of the decline in pass-through than import penetration. However, with shorter lag length, pass-through overall is lower. Tables H.9 to H.11 present results from the same regression where we do not interact the terms with the labor share. We find qualitatively similar results.

Finally, figure H.2 plots the change in import penetration from China between 1997 and 2012 against market concentration in 2012. We find a positive relationship between import competition and concentration, as in the main text where we used overall import penetration.

Table H.1: Pass-Through and Import Penetration ($h = 4$)

	No Labor Share			Labor Share		
Δ PPI	(1) Δ IP	(2) 50th Pct	(3) 75th Pct	(4) Δ IP	(5) 50th Pct	(6) 75th Pct
Δ Wage	0.00643					
	(0.0156)					
Δ TFP	-0.166***	-0.166***	-0.164***	-0.177***	-0.174***	-0.177***
	(0.0244)	(0.0245)	(0.0242)	(0.0242)	(0.0249)	(0.0239)
Δ Wage × Δ IP	-0.0571					
	(0.0540)					
Δ Wage × Low IP		0.0112	0.00938			
		(0.0154)	(0.0160)			
Δ Wage × High IP		-0.0165	-0.0312			
		(0.0185)	(0.0231)			
Δ Wage × LS				0.105		
				(0.114)		
Δ Wage × LS × Δ IP				-0.622**		
				(0.283)		
Δ Wage × LS × Low IP					0.239*	0.172
					(0.123)	(0.116)
Δ Wage × LS × High IP					-0.228	-0.373**
					(0.141)	(0.171)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0401	0.0387	0.0389	0.0459	0.0434	0.0456
Observations	12225	12225	12225	12225	12225	12225

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (20), where the changes in wages, in TFP, and in the PPI are computed over a 4-quarter period, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results from specification (20). We omit the coefficient on ΔIP by itself for brevity. In column 2, we replace the continuous measure of IP by a dummy indicating whether an industry's ΔIP in the given year is above the median of ΔIP, and include two dummies for below and above median IP interacted with the wage change. Column 3 is analogous but using the 75th percentile. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. The regression in column 4 includes a control for the labor share by itself, the labor share interacted with ΔIP, and ΔIP, which we omit for brevity. We similarly include in columns 5-6 the labor share interacted with dummies for above and below median IP and one of these dummies by itself. R-squared is the Within R-squared excluding fixed effects.

Table H.2: Pass-Through and Import Penetration ($h = 12$)

	No Labor Share			Labor Share		
Δ PPI	(1) Δ IP	(2) 50th Pct	(3) 75th Pct	(4) Δ IP	(5) 50th Pct	(6) 75th Pct
Δ Wage	0.0675***					
	(0.0227)					
Δ TFP	-0.169***	-0.175***	-0.158***	-0.199***	-0.197***	-0.192***
	(0.0170)	(0.0171)	(0.0170)	(0.0178)	(0.0189)	(0.0168)
Δ Wage × Δ IP	-0.221**					
	(0.0873)					
Δ Wage × Low IP		0.0824***	0.0820***			
		(0.0291)	(0.0217)			
Δ Wage × High IP		-0.0131	-0.0872*			
		(0.0359)	(0.0513)			
Δ Wage × LS				0.767***		
				(0.157)		
Δ Wage × LS × Δ IP				-1.482***		
				(0.484)		
Δ Wage × LS × Low IP					0.907***	0.960***
					(0.209)	(0.176)
Δ Wage × LS × High IP					0.142	-0.463
					(0.233)	(0.368)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0542	0.0538	0.0526	0.0751	0.0702	0.0755
Observations	10488	10488	10488	10488	10488	10488

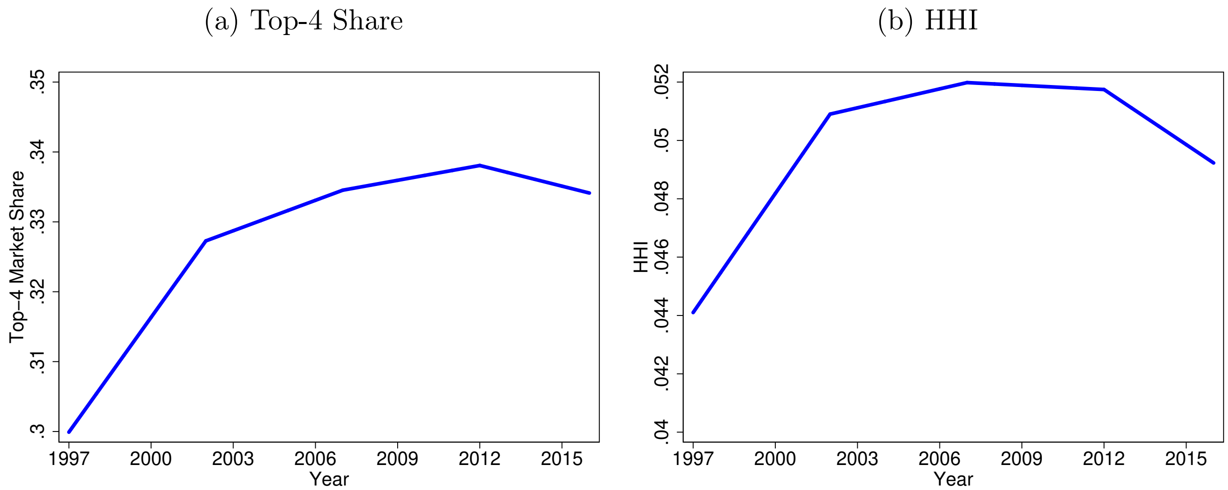
Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (20), where the changes in wages, in TFP, and in the PPI are computed over a 12-quarter period, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results from specification (20). We omit the coefficient on ΔIP by itself for brevity. In column 2, we replace the continuous measure of IP by a dummy indicating whether an industry's ΔIP in the given year is above the median of ΔIP, and include two dummies for below and above median IP interacted with the wage change. Column 3 is analogous but using the 75th percentile. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. The regression in column 4 includes a control for the labor share by itself, the labor share interacted with ΔIP, and ΔIP, which we omit for brevity. We similarly include in columns 5-6 the labor share interacted with dummies for above and below median IP and one of these dummies by itself. R-squared is the Within R-squared excluding fixed effects.

Table H.3: Pass-Through and Import Penetration from China

	No Labor Share			Labor Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ PPI	$h = 4$	$h = 8$	$h = 12$	$h = 4$	$h = 8$	$h = 12$
Δ Wage	-0.000538	0.0144	0.0333			
	(0.0142)	(0.0222)	(0.0256)			
Δ TFP	-0.165***	-0.186***	-0.166***	-0.178***	-0.218***	-0.203***
	(0.0242)	(0.0205)	(0.0170)	(0.0245)	(0.0218)	(0.0182)
Δ Wage $\times$ Δ IP	-0.111	-0.0945	-0.138			
	(0.0709)	(0.0991)	(0.117)			
Δ Wage $\times$ LS				0.0313	0.278	0.651***
				(0.114)	(0.172)	(0.161)
Δ Wage $\times$ LS $\times$ Δ IP				-0.527*	-0.988***	-2.054***
				(0.266)	(0.274)	(0.381)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0389	0.0480	0.0465	0.0461	0.0677	0.0758
Observations	12225	11353	10488	12225	11353	10488

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. LS refers to labor share. The table presents the estimates from specification (20) using the change in import penetration from China only, where the changes in wages, in TFP, and in the PPI are computed over different periods indicated in the column headers, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Columns 1-3 present the baseline regression results from specification (20) using the change in import penetration from China for different lag lengths h. We omit the coefficient on ΔIP by itself for brevity. The column headers indicate whether the regression is run for a time period of $h = 4$, $h = 8$, or $h = 12$. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. These regressions include a control for the labor share by itself, the labor share interacted with ΔIP, and ΔIP, which we omit for brevity. R-squared is the Within R-squared excluding fixed effects.

Figure H.1: Concentration Trends in Manufacturing



Note: The left panel shows the average market share of the top-4 firms in the manufacturing industries in our sample, obtained from the U.S. Census Bureau. The right panel shows the average Herfindahl-Hirschmann Index (HHI), also obtained from the Census. We interpolate between census years (1997, 2002, 2007, 2012, and 2017) using linear interpolation. Earlier data is unavailable on a NAICS basis.

Table H.4: Pass-Through and Sales Concentration in Manufacturing ($h = 4$)

	No Labor Share			Labor Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ PPI	Top-4	Top-20	HHI	Top-4	Top-20	HHI
Δ Wage	0.0554	0.124*	0.0271			
	(0.0376)	(0.0626)	(0.0299)			
Δ TFP	-0.160***	-0.162***	-0.163***	-0.165***	-0.167***	-0.171***
	(0.0265)	(0.0261)	(0.0274)	(0.0269)	(0.0267)	(0.0279)
Δ Wage × Conc	-0.125**	-0.176**	-0.385			
	(0.0610)	(0.0773)	(0.260)			
Δ Wage × LS				0.427*	0.748**	0.207
				(0.233)	(0.310)	(0.192)
Δ Wage × LS × Conc				-1.285***	-1.283***	-4.395*
				(0.478)	(0.434)	(2.214)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0383	0.0394	0.0394	0.0412	0.0418	0.0426
Observations	10452	10452	9996	10452	10452	9996

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. Conc refers to the concentration measure listed in the column header. Top-4 refers to the sales share of the top 4 firms. Top-20 is defined analogously. HHI is the Herfindahl-Hirschmann Index defined over the top 50 firms in the industry. The table presents the estimates from specification (21), where the changes in wages, in TFP, and in the PPI are computed over a 4-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since sales concentration is only available in census years (1997, 2002, 2007, 2012, 2017), we construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2012. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Columns 1-3 present the baseline regression results from specification (21) using the three concentration measures. We omit the coefficient on $Conc$ by itself for brevity. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. The regressions include a control for the labor share by itself, the labor share interacted with $Conc$, and $Conc$ by itself, which we omit for brevity. R-squared is the Within R-squared excluding fixed effects.

Table H.5: Pass-Through and Sales Concentration in Manufacturing ($h = 12$)

	No Labor Share			Labor Share		
Δ PPI	(1) Top-4	(2) Top-20	(3) HHI	(4) Top-4	(5) Top-20	(6) HHI
Δ Wage	0.236***	0.445***	0.157***			
	(0.0527)	(0.0836)	(0.0423)			
Δ TFP	-0.183***	-0.183***	-0.185***	-0.196***	-0.195***	-0.204***
	(0.0190)	(0.0182)	(0.0186)	(0.0195)	(0.0186)	(0.0199)
Δ Wage × Conc	-0.426***	-0.568***	-1.386***			
	(0.0851)	(0.107)	(0.339)			
Δ Wage × LS				1.421***	2.118***	1.013***
				(0.317)	(0.441)	(0.238)
Δ Wage × LS × Conc				-2.817***	-2.829***	-9.268***
				(0.716)	(0.672)	(2.460)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0644	0.0676	0.0616	0.0745	0.0765	0.0741
Observations	9699	9699	9247	9699	9699	9247

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. Conc refers to the concentration measure listed in the column header. Top-4 refers to the sales share of the top 4 firms. Top-20 is defined analogously. HHI is the Herfindahl-Hirschmann Index defined over the top 50 firms in the industry. The table presents the estimates from specification (21), where the changes in wages, in TFP, and in the PPI are computed over a 12-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since sales concentration is only available in census years (1997, 2002, 2007, 2012, 2017), we construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2012. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Columns 1-3 present the baseline regression results from specification (21) using the three concentration measures. We omit the coefficient on $Conc$ by itself for brevity. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. The regressions include a control for the labor share by itself, the labor share interacted with $Conc$, and $Conc$ by itself, which we omit for brevity. R-squared is the Within R-squared excluding fixed effects.

Table H.6: Pass-Through and Employment Concentration in Manufacturing ($h = 8$)

	No Labor Share			Labor Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ PPI	4 Lags	8 Lags	12 Lags	4 Lags	8 Lags	12 Lags
Δ Wage	0.0838**	0.198***	0.302***			
	(0.0401)	(0.0517)	(0.0582)			
Δ TFP	-0.167***	-0.195***	-0.176***	-0.180***	-0.220***	-0.205***
	(0.0242)	(0.0221)	(0.0190)	(0.0257)	(0.0239)	(0.0197)
Δ Wage × Emp Conc	-0.120*	-0.258***	-0.408***			
	(0.0661)	(0.0888)	(0.101)			
Δ Wage × LS				0.584***	1.158***	1.668***
				(0.203)	(0.264)	(0.280)
Δ Wage × LS × Emp Conc				-1.013**	-1.722***	-2.158***
				(0.419)	(0.507)	(0.563)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0425	0.0585	0.0689	0.0486	0.0735	0.0938
Observations	11666	10761	9863	11666	10761	9863

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. TFP is total factor productivity. LS refers to labor share. Emp Conc refers to the share of employment of the top 20 firms. The table presents the estimates from specification (21), where the changes in wages, in TFP, and in the PPI are computed over an 8-quarter period. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Employment concentration is obtained from the NETS database in each year. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Columns 1-3 present the baseline regression results from specification (21) using the three concentration measures. We omit the coefficient on $EmpConc$ by itself for brevity. Columns 4-6 present the same regressions but we interact the change in wages with the industry-level labor share (LS), defined as payroll divided by industry sales. The regressions include a control for the labor share by itself, the labor share interacted with $EmpConc$, and $Conc$ by itself, which we omit for brevity. R-squared is the Within R-squared excluding fixed effects.

Table H.7: Import Penetration versus Concentration ($h = 4$)

Δ PPI	(1) Baseline	(2) IP Only	(3) Conc Only	(4) Both
Δ Wage × LS × Pre-2003	0.311*	0.370**	1.079***	1.045***
	(0.178)	(0.173)	(0.350)	(0.365)
Δ Wage × LS × Post-2003	-0.323*	-0.227	0.499	0.497
	(0.163)	(0.188)	(0.368)	(0.370)
Δ TFP	-0.163***	-0.168***	-0.165***	-0.170***
	(0.0267)	(0.0261)	(0.0266)	(0.0261)
Δ Wage × LS × Δ IP		-0.339		-0.248
		(0.295)		(0.296)
Δ Wage × LS × Conc			-1.315***	-1.190**
			(0.463)	(0.482)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
R-squared	0.0392	0.0424	0.0410	0.0444
Observations	10452	10452	10452	10452

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. LS refers to labor share. Conc refers to the market share of the top-20 firms. The table presents the estimates from specification (22), where the changes in wages, in TFP, and in the PPI are computed over a 4-quarter period, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. Since sales concentration is only available in census years (1997, 2002, 2007, 2012), we construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2012. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results from specification (22) excluding the terms involving IP or concentration, for the shorter time period 1997-2016. We omit the coefficient on the labor share for brevity. In column 2, we add the terms involving IP, omitting the terms on ΔIP by itself, the labor share, and on ΔIP times the labor share. In column 3 we include only the terms involving concentration, omitting $Conc$ by itself, the labor share, and on $Conc$ times the labor share. In column 4 we finally add all terms involving IP and concentration. R-squared is the Within R-squared excluding fixed effects.

Table H.8: Import Penetration versus Concentration ($h = 12$)

Δ PPI	(1) Baseline	(2) IP Only	(3) Conc Only	(4) Both
Δ Wage $\times$ LS $\times$ Pre-2003	1.110***	1.285***	2.620***	2.526***
	(0.252)	(0.254)	(0.492)	(0.499)
Δ Wage $\times$ LS $\times$ Post-2003	-0.0703	0.120	1.696***	1.628***
	(0.205)	(0.214)	(0.533)	(0.529)
Δ TFP	-0.188***	-0.198***	-0.191***	-0.199***
	(0.0184)	(0.0180)	(0.0182)	(0.0176)
Δ Wage $\times$ LS $\times$ Δ IP		-1.017**		-0.838*
		(0.503)		(0.486)
Δ Wage $\times$ LS $\times$ Conc			-2.831***	-2.450***
			(0.709)	(0.696)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
R-squared	0.0694	0.0799	0.0785	0.0881
Observations	9699	9699	9699	9699

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. LS refers to labor share. Conc refers to the market share of the top-20 firms. The table presents the estimates from specification (22), where the changes in wages, in TFP, and in the PPI are computed over a 12-quarter period, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. Since sales concentration is only available in census years (1997, 2002, 2007, 2012), we construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2012. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results from specification (22) excluding the terms involving IP or concentration, for the shorter time period 1997-2016. We omit the coefficient on the labor share for brevity. In column 2, we add the terms involving IP, omitting the terms on ΔIP by itself, the labor share, and on ΔIP times the labor share. In column 3 we include only the terms involving concentration, omitting $Conc$ by itself, the labor share, and on $Conc$ times the labor share. In column 4 we finally add all terms involving IP and concentration. R-squared is the Within R-squared excluding fixed effects.

Table H.9: Import Penetration versus Concentration without Labor Share ($h = 4$)

Δ PPI	(1) Baseline	(2) IP Only	(3) Conc. Only	(4) Both
Δ Wage × Pre-2003	0.0424**	0.0422**	0.163**	0.163**
	(0.0209)	(0.0211)	(0.0652)	(0.0649)
Δ Wage × Post-2003	-0.0391**	-0.0364	0.0918	0.0979
	(0.0169)	(0.0229)	(0.0650)	(0.0637)
Δ TFP	-0.157***	-0.158***	-0.161***	-0.162***
	(0.0266)	(0.0267)	(0.0261)	(0.0263)
Δ Wage × Δ IP		-0.00654		-0.0188
		(0.0581)		(0.0571)
Δ Wage × Conc			-0.168**	-0.168**
			(0.0787)	(0.0784)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
R-squared	0.0357	0.0367	0.0377	0.0387
Observations	10452	10452	10452	10452

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. Conc refers to the market share of the top-20 firms. The table presents the estimates from specification (22) but without labor share interactions, where the changes in wages, in TFP, and in the PPI are computed over a 4-quarter period, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. Since sales concentration is only available in census years (1997, 2002, 2007, 2012), we construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2012. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results from specification (22) excluding the terms involving IP or concentration, for the shorter time period 1997-2016. In column 2, we add the terms involving IP, omitting the terms on ΔIP by itself. In column 3 we include only the terms involving concentration, omitting $Conc$ by itself. In column 4 we finally add all terms involving IP and concentration. R-squared is the Within R-squared excluding fixed effects.

Table H.10: Import Penetration versus Concentration without Labor Share ($h = 8$)

Δ PPI	(1) Baseline	(2) IP Only	(3) Conc. Only	(4) Both
Δ Wage × Pre-2003	0.0782***	0.0853***	0.361***	0.371***
	(0.0258)	(0.0266)	(0.0783)	(0.0801)
Δ Wage × Post-2003	-0.0563**	-0.0265	0.245***	0.281***
	(0.0281)	(0.0280)	(0.0835)	(0.0840)
Δ TFP	-0.187***	-0.189***	-0.199***	-0.201***
	(0.0226)	(0.0228)	(0.0226)	(0.0228)
Δ Wage × Δ IP		-0.109		-0.129*
		(0.0731)		(0.0744)
Δ Wage × Conc			-0.387***	-0.389***
			(0.0915)	(0.0937)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
R-squared	0.0491	0.0523	0.0584	0.0615
Observations	10042	10042	10042	10042

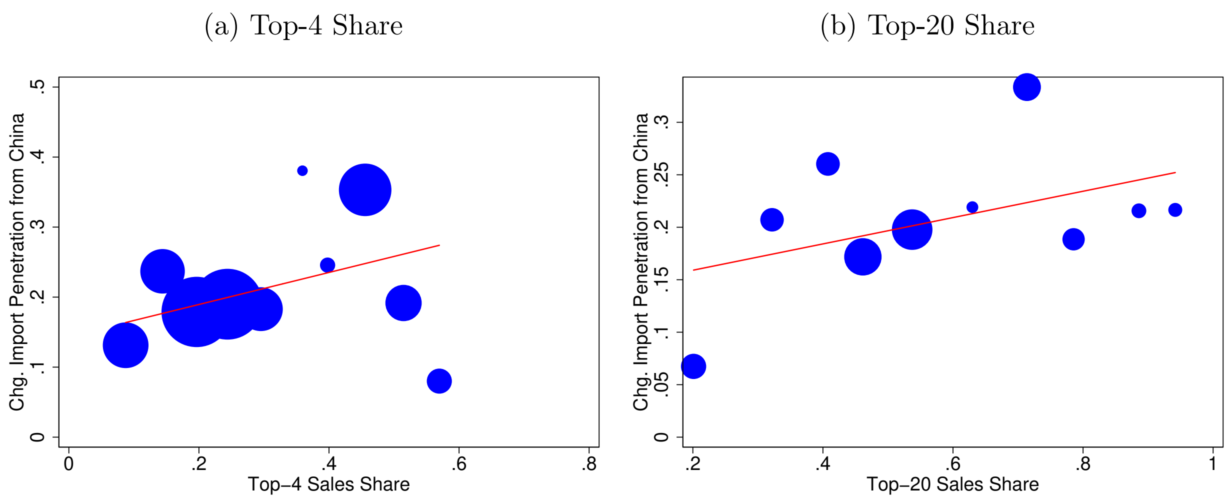
Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. Conc refers to the market share of the top-20 firms. The table presents the estimates from specification (22) but without labor share interactions, where the changes in wages, in TFP, and in the PPI are computed over an 8-quarter period, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. Since sales concentration is only available in census years (1997, 2002, 2007, 2012), we construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2012. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results from specification (22) excluding the terms involving IP or concentration, for the shorter time period 1997-2016. In column 2, we add the terms involving IP, omitting the terms on ΔIP by itself. In column 3 we include only the terms involving concentration, omitting $Conc$ by itself. In column 4 we finally add all terms involving IP and concentration. R-squared is the Within R-squared excluding fixed effects.

Table H.11: Import Penetration versus Concentration without Labor Share ($h = 12$)

Δ PPI	(1) Baseline	(2) IP Only	(3) Conc. Only	(4) Both
Δ Wage $\times$ Pre-2003	0.133***	0.144***	0.554***	0.562***
	(0.0299)	(0.0313)	(0.0877)	(0.0900)
Δ Wage $\times$ Post-2003	-0.0497**	-0.0119	0.404***	0.442***
	(0.0244)	(0.0197)	(0.0841)	(0.0844)
Δ TFP	-0.167***	-0.171***	-0.181***	-0.183***
	(0.0180)	(0.0181)	(0.0183)	(0.0184)
Δ Wage $\times$ Δ IP		-0.154*		-0.177**
		(0.0909)		(0.0884)
Δ Wage $\times$ Conc			-0.587***	-0.580***
			(0.103)	(0.104)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Composition Controls	Yes	Yes	Yes	Yes
R-squared	0.0502	0.0582	0.0691	0.0766
Observations	9699	9699	9699	9699

Notes: *, **, and *** indicate significance at the 90th, 95th, and 99th percent level, respectively. IP refers to import penetration. TFP is total factor productivity. Conc refers to the market share of the top-20 firms. The table presents the estimates from specification (22) but without labor share interactions, where the changes in wages, in TFP, and in the PPI are computed over a 12-quarter period, and the change in IP is computed since 1997. All regressions are run at quarterly frequency, and weighted by an industry's total sales in 2012 from the economic censuses. Since IP is an annual measure, we apply its value to all quarters of the same year. Since sales concentration is only available in census years (1997, 2002, 2007, 2012), we construct the concentration measures in intermittent years via linear interpolation, to obtain concentration series for 1997 to 2012. We include labor force composition controls for the employment shares of middle-aged and older workers, employment shares of those with high school, associate's, or bachelor's degrees, and employment share of female workers. Driscoll-Kraay standard errors with a bandwidth of 2 quarters are shown in parentheses. Column 1 presents the baseline regression results from specification (22) excluding the terms involving IP or concentration, for the shorter time period 1997-2016. In column 2, we add the terms involving IP, omitting the terms on ΔIP by itself. In column 3 we include only the terms involving concentration, omitting $Conc$ by itself. In column 4 we finally add all terms involving IP and concentration. R-squared is the Within R-squared excluding fixed effects.

Figure H.2: Market Concentration versus Import Penetration from China

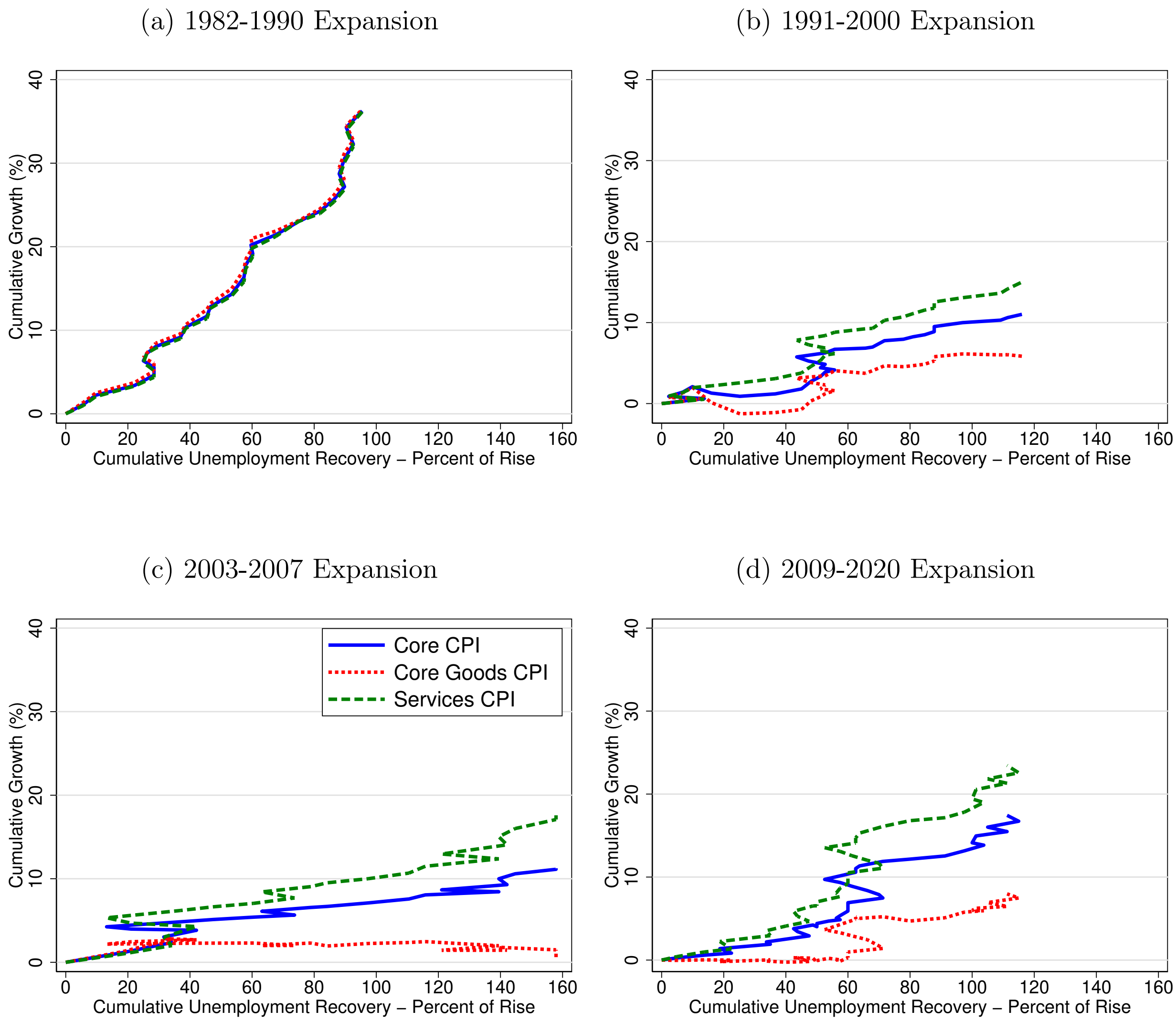


Note: The panels plot the change in import penetration from between 1997 and 2016 against the average concentration over that period for groups of industries. The left panel uses the top-4 sales share, the right panel uses the top-20 sales share as concentration measure. We assign industries to ten groups based on their average concentration, where the groups are uniformly distributed between the minimum and the maximum level of concentration. We then compute the mean change in import penetration from China and the mean concentration for each group. The size of each circle is proportional to the total sales of the given industry group in 2012.

I International Evidence

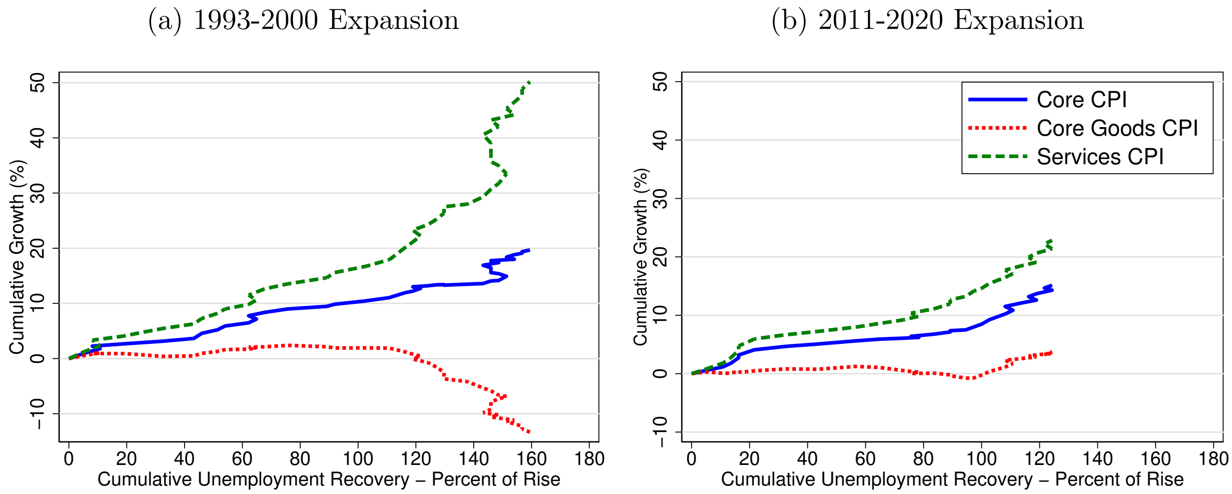
In this section, we show figures of cumulative inflation against the unemployment recovery gap for other countries, analogous to Figure 2 in the main text. Figure I.1 presents inflation for Canada, Figure I.2 shows the same for the United Kingdom, and Figure I.3 for the Euro zone. In all three figures, cumulative goods inflation in the last expansions is significantly more muted than cumulative services inflation.

Figure I.1: Inflation versus Unemployment Recovery from Four Previous Recessions for Canada



Source: Haver Analytics and authors' calculations. Note: The blue line in each panel plots the cumulative core CPI inflation (all items less food and energy, seasonally adjusted) against the unemployment recovery gap measure defined in the text, starting at peak unemployment of a given recession. The red dotted line shows the core goods CPI (commodities less food and energy commodities, seasonally adjusted) and the green dashed line presents core services CPI (services less energy services, seasonally adjusted).

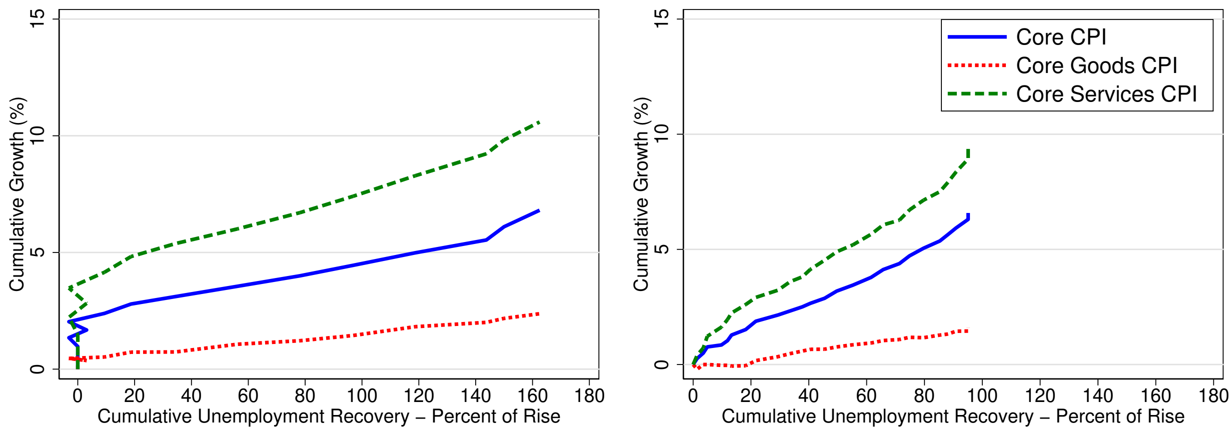
Figure I.2: Inflation versus Unemployment Recovery from Two Previous Recessions for the UK



Source: Haver Analytics and authors' calculations. Note: The blue line in each panel plots the cumulative core CPI inflation (all items less food and energy, seasonally adjusted) against the unemployment recovery gap measure defined in the text, starting at peak unemployment of a given recession. The red dotted line shows the core goods CPI (commodities less food and energy commodities, seasonally adjusted) and the green dashed line presents core services CPI (services less energy services, seasonally adjusted).

Figure I.3: Inflation versus Unemployment Recovery from Two Previous Recessions for the Eurozone

(a) 1993-2000 Expansion (b) 2011-2020 Expansion



Source: Haver Analytics and authors' calculations. Note: The blue line in each panel plots the cumulative core CPI inflation (all items less food and energy, seasonally adjusted) against the unemployment recovery gap measure defined in the text, starting at peak unemployment of a given recession. The red dotted line shows the core goods CPI (commodities less food and energy commodities, seasonally adjusted) and the green dashed line presents core services CPI (services less energy services, seasonally adjusted).