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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.

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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 the missing inflation can be accounted for by the declining pass-through from wages to prices in the goods-producing sector. We attribute this decline 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 these 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.

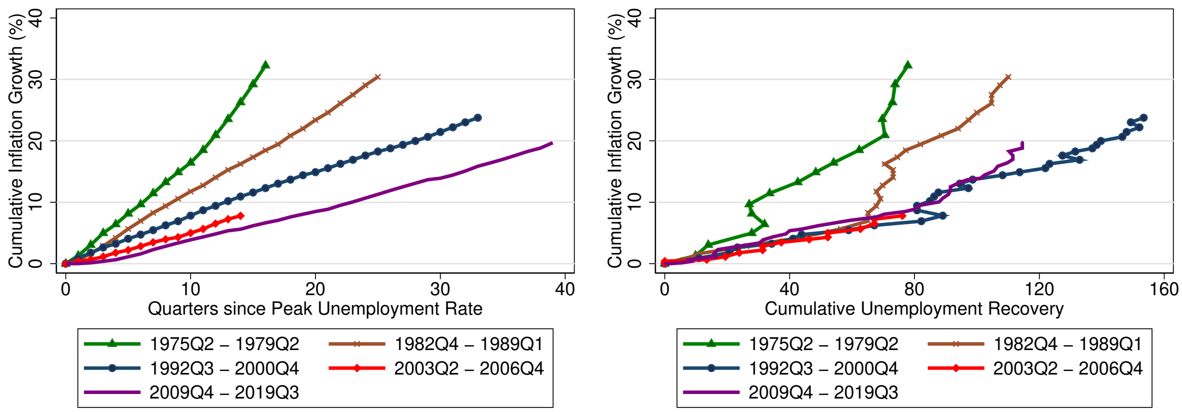
While the evolution of consumer price inflation over time is informative, the duration of expansions is an increasingly misleading indicator of labor market recovery given the emergence of jobless recoveries. We therefore propose a novel but simple measure of labor market recovery that is consistent 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 with inflation picking up rapidly after the end of the recessions. The three most recent

[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 (2019). 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 CPI Inflation During Economic Expansions

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



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 whether inflation in goods or in services is primarily responsible for the slowdown in consumer price inflation and identify core goods inflation as the main driver of the change in inflation dynamics. 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 most recent expansion. At the same time, the recovery of core services inflation has been roughly similar in all expansions. We analyze a counterfactual scenario in which goods prices behaved in the 2009-2020 expansion in the same way as they did during the 1982-89 expansion, and show that around 50% of the missing inflation relative to the 1980s expansion can be traced to goods prices. 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 recessions. 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 the 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.

Our paper proposes two potential 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 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 the wage shock. As a result, fewer firms are compelled to adjust their price, causing domestic firms to absorb more of the shock into their markup in order to preserve market share against their foreign competitors. The model thus predicts that rising import penetration reduces pass-through. 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 various data sources. 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 manufacturing and services industries separately in our disaggregated data. We find that pass-through is significant in services industries for up to seven quarters but insignificant or negative in manufacturing. Over a one-year horizon, we find that there is essentially no pass-through from wages to producer prices in manufacturing, while we estimate a pass-through of about 10% in services using an OLS estimation. This result implies that a 10% increase in labor costs is associated with a 1.0% increase in service prices.

As highlighted by our theory, an important caveat for interpreting the OLS pass-through coefficients is that the source of the wage growth could reflect improvements in productivity.[3] In that case, wage growth does not constitute a cost-push shock for firms and therefore does not need to pass through to prices. We address this concern using two approaches. First, we control for productivity and find that including this control does not change our main finding. Second, we consider an instrumental-variables approach. The instrument we choose is the job-to-job transitions rate. This choice builds on the insights in Moscarini and Postel-Vinay (2017a), who show using a job-ladder model that inflationary wage growth arises when firms try to poach employees of other firms, since poachers bid up the wages of employed workers and incumbents raise wages to increase retention. We build on the empirical work of Karahan et al. (2017) and Moscarini and Postel-Vinay (2017b), and use the realized job-to-job transitions as instrument. The exclusion restriction behind this instrument is that the competition between workers does not affect prices directly, for example by affecting firms' productivity; wages are affected due to competition and prices only due to increasing unit labor costs. We find high and positive pass-through for services but insignificant and negative pass-through for manufacturing.

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 three decades, consistent with the rise in trade and concentration during that period. While pass-through was positive and significant 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-price pass-through. We focus specifically on import competition from China, based on the well-documented effects of Chinese entrants on competition and employment (Gutiérrez and Philippon (2017), Autor et al. (2013)). Our empirical results imply that while an industry with no imports from China exhibits a pass-through from wages to prices of about 2.5%, pass-through would be cut in half in an industry in which the share of sales originating from China is 10%. 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 a 14% price increase in a perfectly competitive industry, it would only correspond to a 4% price increase in an industry where top-4 firms market share is 50%. While our empirical strategy cannot distinguish between the import penetration and market concentration channels, we document that they are positively correlated across industries, suggesting that both could reflect the same underlying

[3] A long-standing literature addresses the various conceptual and econometric difficulties of pass-through regressions more generally, mostly in the context of exchange-rate pass-through. See for example, Campa and Goldberg (2005) and Nakamura and Zerom (2010).

mechanism as argued by Amiti and Heise (2020). Coupled with rising import penetration and market concentration over the last decades, these findings offer an explanation for the declining pass-through.

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)). 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 price 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. Del Negro et al. (2015), Carvalho et al. (2017), Coibion and Gorodnichenko (2015), 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. Our analysis complements these papers by explicitly focusing on the disappearing pass-through from wages to prices in the goods sector and 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 slower pick-up of the consumer price inflation during expansions is largely attributable to the changing behavior of goods prices. 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/unemployment dynamics (see, for example, Jaimovich and Siu (2012) or Galí et al. (2012)). 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

$$URecovery_t = \frac{u_{peak} - u_t}{u_{peak} - u_{trough}}. \tag{1}$$

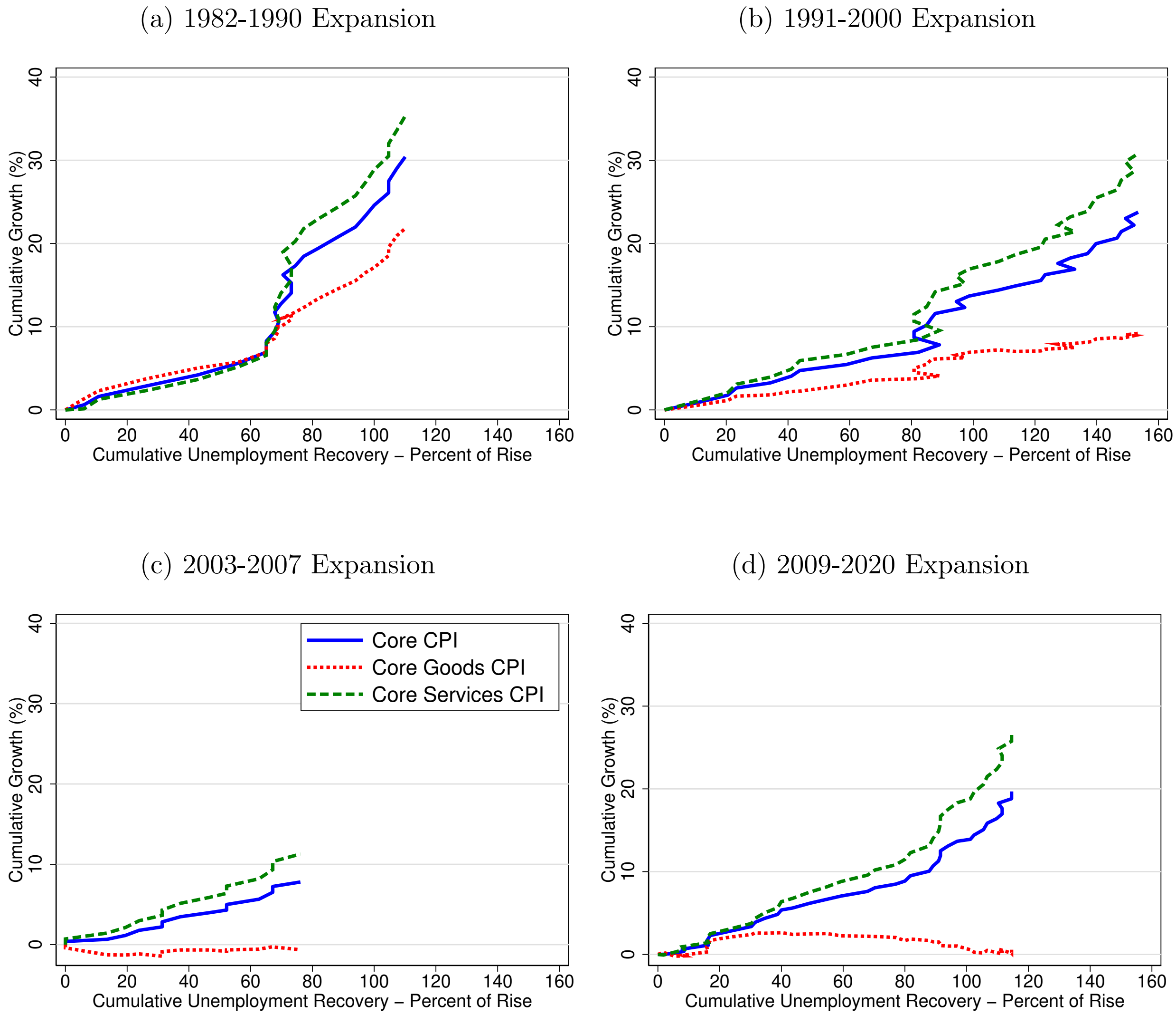
For example, a value of one indicates that the unemployment rate is back to its pre-recession trough. As is well documented, $URecovery_t$ takes longer to achieve in more recent expansions, consistent with the emergence of jobless recoveries. Our new measure captures the fact that employment-output dynamics 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.[4]

This figure establishes our first fact: Growth in core goods prices has slowed notably over

[4] 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 goods 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.

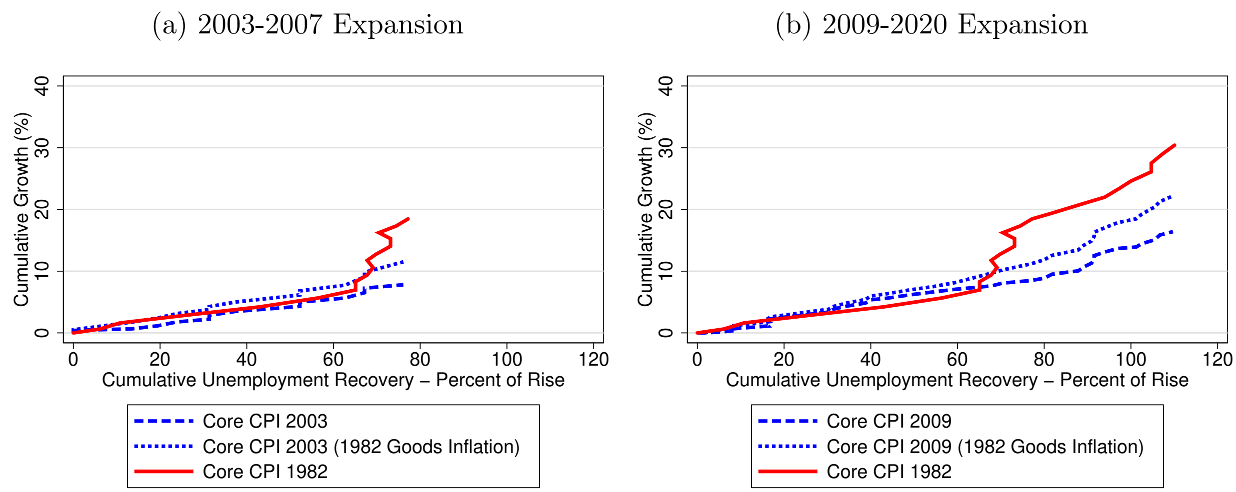
Figure 2: Inflation versus Unemployment Recovery from Four Previous Recessions



time and accounts for a large share of the weakening inflation-unemployment relationship 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 also construct analogous sets of figures for three alternative measures of recovery in Appendix C and show that our finding is robust to these other measures. Figure A.1 shows the cumulative price growth against the cumulative GDP growth since peak unemployment and Figure A.2 plots price growth against time since peak unemployment. Figure A.3 shows price growth against the recovery of the employment-to-population ratio from its recessionary

Figure 3: Counterfactual Inflation for the 2003-2007 and 2009-2020 expansions using core goods inflation in 1982.



trough. All three figures paint a similar picture as Figure 2.

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 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. This finding implies that the behavior of core goods inflation is the key to understanding the changing behavior of inflation.

Role of Labor Costs

One possibility is the differential behavior of labor costs in for goods and 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).[5] 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.

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

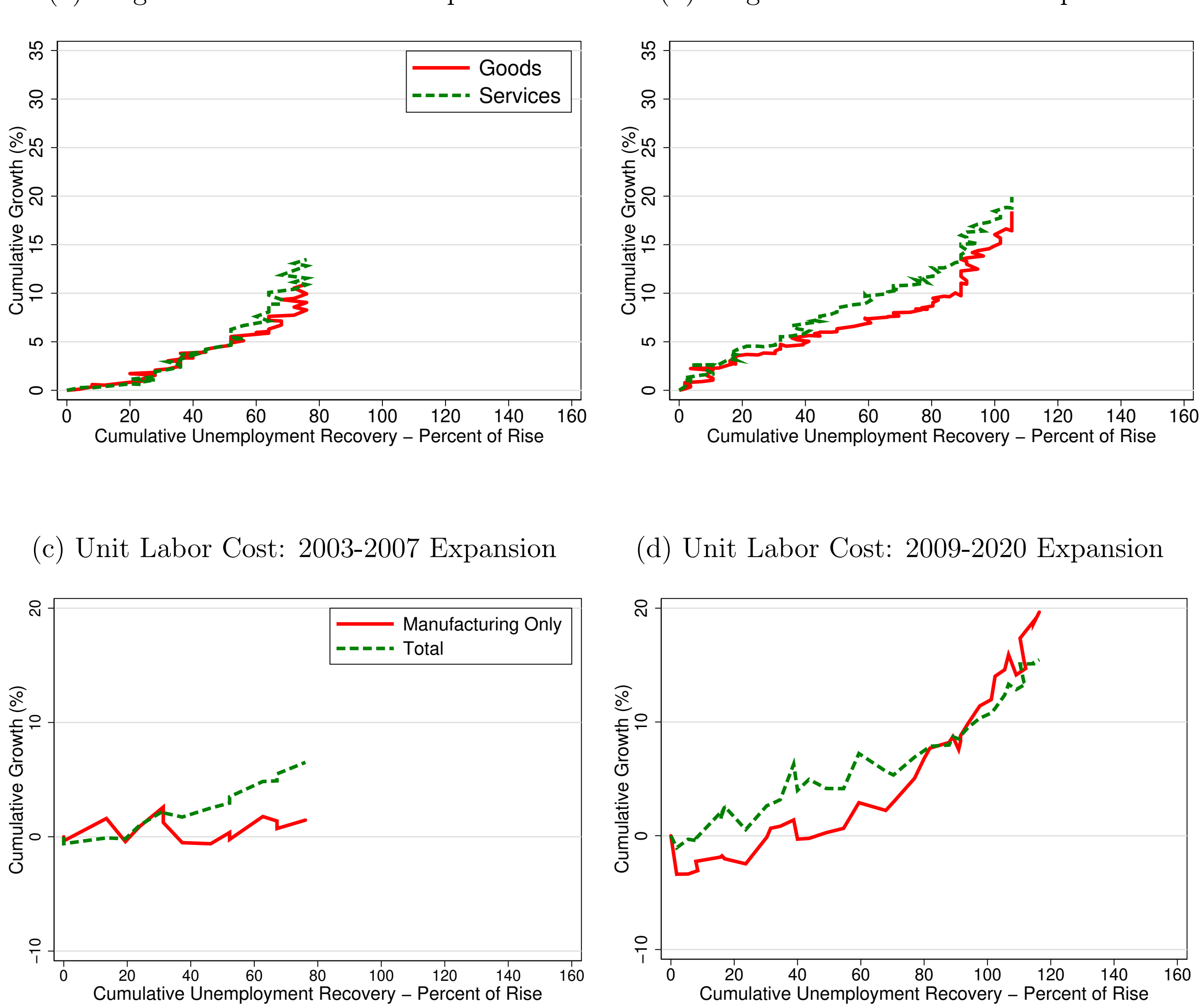
Figure 4: Cumulative growth in wages (top panels) and in unit labor costs (bottom panels) relative to unemployment recovery gap

(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



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. Therefore, lack of a pick-up in goods inflation is not puzzling. 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 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 examine directly next. .

Role of Pass-trough from Wages to Prices

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

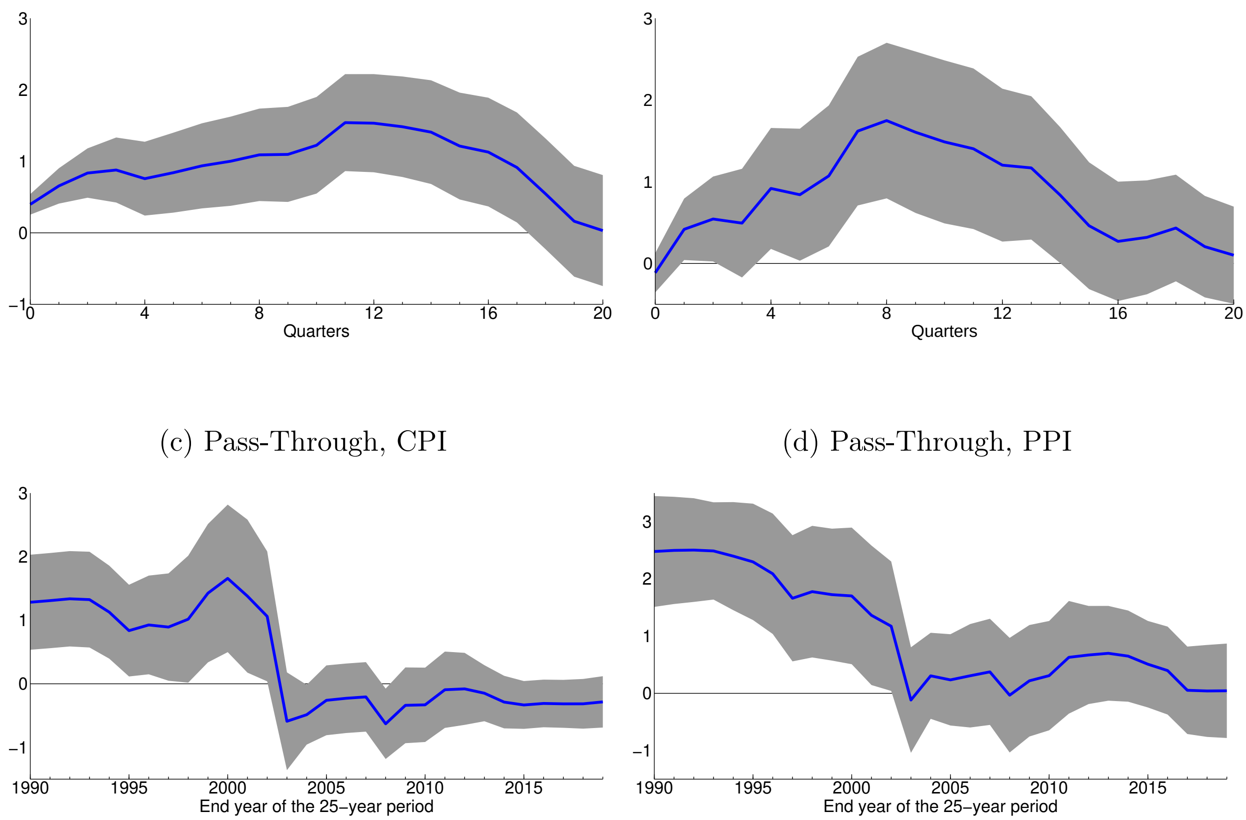
$$\pi_{t+h}^{\text{price}} = \alpha + \beta_h \pi_t^{\text{wage}} + \sum_{j=1}^{8} \delta_j \pi_{t-j}^{\text{price}} + \sum_{j=1}^{8} \zeta_j \pi_{t-j}^{\text{wage}} + \eta z_t + \epsilon_t, \tag{2}$$

where π_{t+h}^{price} is price inflation in quarter $t+h$, π_t^{wage} is wage inflation in quarter t, and z_t is a control for the unemployment gap to capture that price inflation will be lower when the unemployment gap is higher. We measure price inflation based on two measures: 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. 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 responses of an innovation in average hourly earnings on both the Core CPI and the Core PPI, respectively. We find a strong positive pass-through of wage changes to both the CPI and the PPI, which rises and peaks at about 11 quarters for the CPI and at 8 quarters for the PPI. We next estimate pass-through over 25-year rolling windows and plot the resulting peak pass-through in figures 5c and 5d at different points in time. The figures highlight that both for the CPI and the PPI pass-through has declined significantly. Pass-through was significant and positive until the early 2000s, then dropped sharply and is currently indistinguishable from zero.

While our aggregate pass-through estimates show a stark decline in pass-through, they have two main shortcomings. First, we cannot distinguish the exact 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 within-industry variation using detailed data on wages and prices.

Figure 5: Aggregate Pass-Through



(a) Impulse Response of CPI to Earnings

(b) Impulse Response of PPI to Earnings

(c) Pass-Through, CPI

(d) Pass-Through, PPI

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 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 is negligible, while it remains significant and positive in services.

3.1 A Framework Linking Pass-Through and Competition

Our setup follows closely the framework developed in Atkeson and Burstein (2008). 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. To focus on pass-through and to facilitate the model's exposition, we do not explicitly model a household sector.

3.1.1 Setup

There are two sectors, goods and services. Production in each sector is carried out by a competitive firm using the output of a continuum of industries $k \in [0,1]$, which are aggregated according to the CES production function

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

where $y_s(k)$ denotes the output produced by industry k in sector $s \in \{G, S\}$ and σ is the elasticity of substitution between industries. Standard arguments imply that the demand curve for goods of industry k is then obtained as

$$y_s(k) = \left(\frac{p_s(k)}{P_s} \right)^{-\sigma} Y_s, \tag{4}$$

where $P_s = (\int_0^1 p_s(k)^{1-\sigma} dk)^{1/(1-\sigma)}$.

Each industry is populated by a finite number of firms, $N_s(k)$, which are indexed by i. These firms can either be foreign or domestic. The industry-specific aggregator of varieties is given by

$$y_s(k) = \left(\sum_{i=1}^{N_s(k)} y_s(k,i)^{(\eta-1)/\eta} \right)^{\eta/(\eta-1)}, \tag{5}$$

where η is the elasticity of substitution across varieties, and $y_s(k,i)$ is the quantity of firm i's variety in industry k. The demand for variety (k,i) is then given by

$$y_s(k,i) = p_s(k,i)^{-\eta} p_s(k)^{\eta-\sigma} P_s^{-\sigma} Y_s, \tag{6}$$

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

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

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

where A is total factor productivity, l is labor, and k is capital. Standard cost minimization formulates the marginal cost of the firm to produce $y_s(k,i)$ amount of output as a function of wage, w, and the rental rate of capital, r, as

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

Factor prices are determined competitively and taken as given by each firm.[6] We allow wages to be potentially different for domestic and foreign firms; in particular, below we will study wage shocks that only affect domestic firms.

As in Atkeson and Burstein (2008), we assume that varieties are more substitutible across 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 $p_s(k)$. Firms therefore face an effective elasticity of demand of

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

where $\varphi_s(k,i) = (p_s(k,i)y_s(k,i))/(\sum_{i'} p_s(k,i')y_s(k,i'))$ 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

Each firm solves

$$\max_p \left[p_s(k,i) - c_s(k,i)\right] \left(\frac{p_s(k,i)}{p_s(k)}\right)^{-\eta} \left(\frac{p_s(k)}{P_s}\right)^{-\sigma} Y_s, \tag{10}$$

where $c_s(k,i)$ is the marginal cost of firm c in industry k. 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

$$p_s(k,i) = \frac{\mathcal{E}_s(k,i)}{\mathcal{E}_s(k,i) - 1} c_s(k,i), \tag{11}$$

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

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

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

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

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

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

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

$$d \log p_s(k,i) = -\Gamma_s(k,i) \left[d \log p_s(k,i) - d \log p_s(k) \right] - d \log A + \alpha d \log w_i, \tag{14}$$

where we have assumed that r is constant. Solving this equation for $d \log p_s(k,i)$, we find

$$d \log p_s(k,i) = \frac{\Gamma_s(k,i)}{1+\Gamma_s(k,i)} d \log p_s(k) - \frac{1}{1+\Gamma_s(k,i)} d \log A + \frac{\alpha}{1+\Gamma_s(k,i)} d \log w_i. \tag{15}$$

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, $p_s(k)$. The relative strength of the two channels is modulated by the markup elasticity $\Gamma_s(k,i)$. 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, $d\Gamma_s(k,i)/d\varphi_s(k,i) > 0$, and satisfies $\Gamma_s(k,i) = 0$ if $\varphi_s(k,i) = 0$. Equivalently, if all firms in an industry have the same market share, $\varphi_s(k,i) = 1/N_s(k)$, then $d\Gamma_s(k,i)/dN_s(k) < 0$. 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, assuming that foreign firms do not experience domestic wage shocks, 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, $p_s(k)$, 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 $p_s(k,i)$ 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 $\Gamma_s(k,i)$ 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 $p_s(k)$ 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 $N_D \geq 1$ domestic firms and $N_F \geq 1$ foreign firms with symmetric market shares. Consider a wage shock which only affects domestic firms.*

1. *If $N_D + N_F = N < \infty$, pass-through is less than α. Holding fixed the ratio N_D/N, a decline in N leads to a reduction in pass-through.*

2. *A higher share of domestic firms in the industry, N_D/N, increases pass-through.*

Proof. See Appendix A.2. □

Our empirical analysis is built on these insights and rely 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. As a first step, we implement our estimating equation (12) using the same local projection framework as before. We then estimate standard pass-through regressions at an annual horizon and examine the role of the labor share and the causal impact of wages on prices.

3.2.1 Pass-through estimates: Local Projections

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

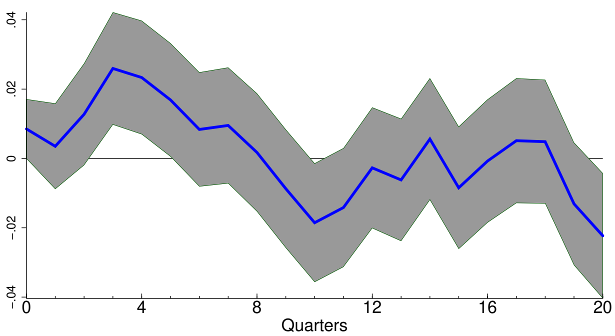
$$\Delta \ln(p_{i,t+h}) = \alpha + \beta_h \Delta \ln(w_{it}) + \sum_{j=1}^{8} \delta_j \Delta \ln(p_{i,t-j}) + \sum_{j=1}^{8} \zeta_j \Delta \ln(w_{i,t-j}) + \eta X_{it} + \xi_i + \rho_t + \epsilon_{it}, \quad (16)$$

where p_{it} is the producer price index in industry i and period t, w_{it} is the industry's wage index, and X_{it} is a set of time-varying controls such as the change in TFP as emphasized in our theoretical specification above. 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. 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 work force. The coefficient β_h captures the pass-through of wage changes to price changes h quarters ahead. 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.

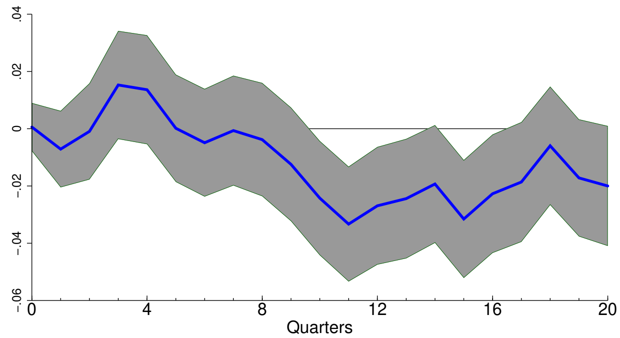
Our empirical implementation combines several publicly available datasets. For price data, we use the seasonally-adjusted, industry-level Producer Price Index (PPI) series from the BLS. We analyze producer prices in this section because producer prices are available at the industry-level, allowing for a clean mapping between industry-level wages and prices. Moreover, as shown above, 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.[7] 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. Our baseline pass-through dataset combines the price and the 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 information for 255 5-digit industries, of which 148 are in manufacturing. The first available year where we have price information for goods and services is 2003. We exclude petroleum and coal products (NAICS 324) from all analyses. Appendix B provides more details.

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

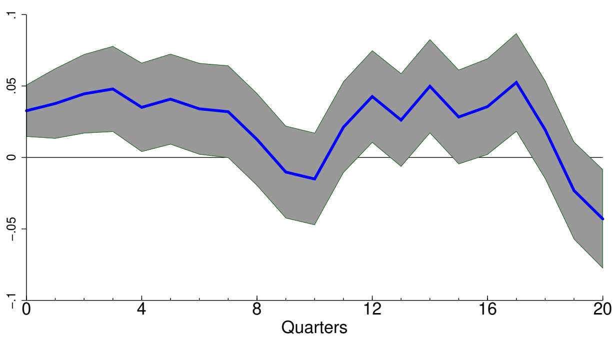
Figure 6: Impulse Response Functions



(a) Manufacturing and Services



(b) Manufacturing



(c) Services

To estimate the regression in (16), we compute the four quarter log change in each industry's producer price index, $\Delta \ln(p_{it})$, the four quarter log change in wages, $\Delta \ln(w_{it})$, and the four quarter log change in TFP, $\Delta \ln(A_{it})$.

The top left panel of Figure 6 shows the estimated impulse response function using all industries in our dataset. 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 6 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 6 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.

3.2.2 Pass-through estimates: Regression Analysis

For the remainder of the paper, we focus on a simpler specification and estimate contemporaneous pass-through at $h = 0$. This specification will allow us to more easily add different interaction terms and control variables going forward, and maps directly into our theoretical specification above. Specifically, we estimate

$$\Delta \ln(p_{it}) = \beta \Delta \ln(w_{it}) + \gamma X_{it} + \delta_i + \rho_t + \epsilon_{it}. \tag{17}$$

We weight the regression by an industry's total sales in 2012, and use Driscoll-Kraay standard errors to account for cross-sectional and time series correlation.

Table 1 presents the results. As before, we initially do not separate between goods and services. The results in Column (1) show that in this specification the contemporaneous pass-through from wage changes to price changes is about 0.06. As expected, an increase in productivity has a negative effect on price changes. A 10% increase in productivity translates to a 0.8% decline in price growth. Column (2) includes separately coefficients for wage growth in manufacturing and 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 0.10 in services, confirming our earlier finding. Importantly, the pass-through of wages to prices is relatively unchanged when controlling for productivity.

Clearly, the interpretation of the pass-through coefficient is subject to several concerns. One important concern is related to the measure of labor costs. Wage growth represents an increase in labor costs to firms only to the extent that labor is used in firms operating in that industry and is not substitutable in the short run. In the simple model derived above, even if markups and productivity are constant, wage changes translate to a price change only to the extent of the industry's share of labor in total output, which is given by α. Through this lens, the lower pass-through rates estimated for manufacturing in Columns (1)–(3) might be due to differences in labor's share in output across industries rather than due to differences in pricing behavior.

To address this concern, 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 given year based on the Annual Survey of Manufacturers (ASM) from 2003-

Table 1: Pass-Through Regressions for Goods versus Services

	(1) Aggregate	(2) No TFP	(3) With TFP	(4) Aggregate	(5) No TFP	(6) With TFP
Δ Wage	0.0616***					
	(0.0167)					
Δ TFP	-0.0793***		-0.0757***	-0.0788***		-0.0778***
	(0.0149)		(0.0141)	(0.0155)		(0.0155)
Δ Wage Manuf		0.0107	0.0216			
		(0.0179)	(0.0186)			
Δ Wage Services		0.102***	0.0917***			
		(0.0323)	(0.0286)			
Δ Wage × LS				0.182**		
				(0.0760)		
Δ Wage × LS Manuf					-0.0642	0.0581
					(0.107)	(0.108)
Δ Wage × LS Services					0.242**	0.197**
					(0.103)	(0.0852)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.0184	0.0116	0.0197	0.0169	0.00863	0.0170
Observations	12727	12727	12727	12727	12727	12727

TFP is total factor productivity. LS refers to the labor share. Driscoll-Kraay standard errors in parentheses. All regressions are weighted by an industry's total sales in 2012.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 then estimate

$$\Delta \ln(p_{it}) = \beta \alpha_{it} \Delta \ln(w_{it}) + \gamma X_{it} + \delta_i + \rho_t + \epsilon_{it}. \tag{18}$$

This regression controls for heterogeneity in labor shares across industries. If pass-through in each industry was equal to the 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 simply due to a lower labor share in that sector. When we do not differentiate between manufacturing and services, we find a pass-through of 18% in column

(4). When we estimate them separately, we find a pass-through of 20% in services (when controlling for productivity), implying that a 10% increase in labor costs is associated with a 2% increase in service prices in an industry that uses only labor. The pass-through in manufacturing is still estimated to be small and insignificant. Table A.1 in Appendix D shows that not weighting the observations by sales in 2012 produces similar results. Table A.2 in Appendix D shows that the results are similar when we do not include industry or time fixed effects.

Identifying the Causal Effect of Labor Costs on Prices

A second concern is regarding the interpretation of β as the causal effect of labor costs on prices. Wage growth can be driven by various factors such as changes in worker composition, improvements in labor productivity, and increases in labor demand in tight labor markets. Only the part of wage growth that is in excess of productivity growth constitutes a cost push shock to the firm. We next try to isolate the *inflationary component of wage growth* and measure the response of prices to the cost-push shock we identify exploiting an instrumental variable approach.

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

Table 2: IV Regressions

	(1)	(2)	(3)	(4)
	Services		Manufacturing	
	Δ Wage	Δ Price	Δ Wage	Δ Price
Δ TFP	-0.0622	0.0223	0.0544***	-0.0190
	(0.0522)	(0.0528)	(0.0199)	(0.253)
J2J	1.030**		4.940	
	(0.521)		(7.205)	
Δ Wage Services		1.234**		
		(0.560)		
Δ Wage Manuf				-2.699
				(4.138)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
R2		-1.087		-7.055
Observations	4994	4994	7730	7730
F-Statistic	15.82		3.49	

TFP is total factor productivity. Driscoll-Kraay standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

rates from the Longitudinal Employer Household-Dynamics (LEHD).[8] 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 (17) via instrumental variables, separately for goods and for services, where we instrument for the wage change of industry i in sector $\mathcal{S}$ with the first-stage regression

$$\Delta w_{it}^{\mathcal{S}} = \beta^{\mathcal{S}} JtoJ_{it}^{\mathcal{S}} + \gamma^{\mathcal{S}} X_{it}^{\mathcal{S}} + \delta_i^{\mathcal{S}} + \rho_t^{\mathcal{S}} + \epsilon_{it}^{\mathcal{S}}, \tag{19}$$

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

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 2 show that job-to-job transitions are a good instrument for the change in wages in the services sector. 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 2 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.[9]

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 (17).

Table 3 presents our findings. The first column shows that over the extended period, the average pass-through is positive but very small. In the second column, we allow the pass-through coefficient to vary over time. Specifically, we estimate the effect for the periods before and after 2003 by interacting the wage change with a dummy for these periods. Our results indicate a sizable change in the price pass-through: For the period prior to 2003, increases in wages did translate into increases in 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 find a pass-through of 31% 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

[9]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 3: Pass-Through Regressions in Manufacturing

	(1) All	(2) Pre/Post	(3) All	(4) Pre/Post
Δ Wage	0.0223			
	(0.0135)			
Δ TFP	-0.169***	-0.167***	-0.179***	-0.177***
	(0.0193)	(0.0192)	(0.0196)	(0.0195)
Δ Wage × Pre-2003		0.0471**		
		(0.0182)		
Δ Wage × Post-2003		-0.0000794		
		(0.0182)		
Δ Wage × LS			0.140	
			(0.106)	
Δ Wage × LS × Pre-2003				0.311**
				(0.138)
Δ Wage × LS × Post-2003				-0.0607
				(0.155)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
R2	0.0372	0.0350	0.0431	0.0418
Observations	12913	12913	12913	12913

TFP is total factor productivity. Driscoll-Kraay standard errors in parentheses.
Columns (2) and (4) include interactions with a dummy variable for the year being before or after 2009.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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.

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. We estimate pass-through to be around 25 percent per unit of labor using an OLS specification. Using an instrumental variables approach, we find complete pass-through. Second, we estimate very little or no pass-through from labor costs to prices in manufacturing in the post-2003 period. 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 30 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 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 of the 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 China's WTO entry in the early 2000s (e.g., Autor et al. (2013)). This literature has documented substantial effects of Chinese 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 from China in the average 5-digit NAICS industry in our sample in the U.S. manufacturing sector over time. While in the early 1990s imports from China accounted for only about 1% of sales in the average manufacturing industry in the U.S., imports from China rose to about 10% of total manufacturing sales in 2016.[10] 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.

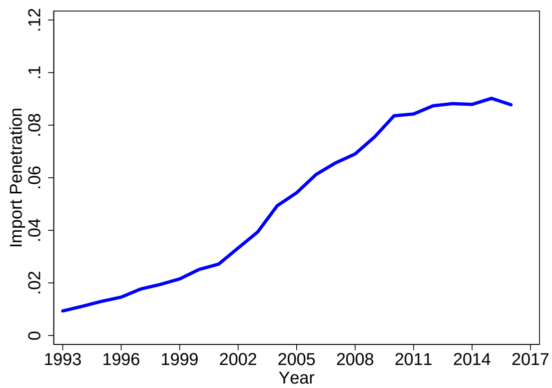
A second important change in the U.S. economy is the rising market concentration as documented by Autor et al. (2020). Figure 7b shows the sales share of top 20 firms in the manufacturing sector.[11] There was a gradual increase in the concentration of sales in top

[10] Autor et al. (2013) and Pierce and Schott (2016) show that the sharp increase in imports from China over this period led to a significant decline in employment in the manufacturing sector.

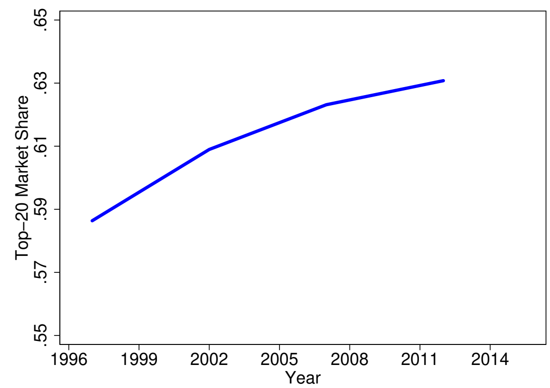
[11] Figures A.9a and A.9b in Appendix B show that the patterns are similar for the sales share of the top 4 firms and the HHI.

Figure 7: Rising import penetration and concentration in the manufacturing sector

(a) Import Penetration from China



(b) Concentration



20 firms over time. 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 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 level of import penetration from China. Specifically, we compute import penetration of industry i as

$$IP_{it}^{CN} = \frac{\text{Imports}_{it}^{CN}}{\text{Sales}_{it} - \text{Exports}_{it} + \text{Imports}_{it}}, \tag{20}$$

where Imports_{it}^{CN} are imports by industry i from China in year t, Imports_{it} and Exports_{it} are the industry's total imports and exports, respectively, and Sales_{it} are the total sales in that industry. We obtain imports and exports for each NAICS industry each year from the

U.S. Census Bureau, available via Peter Schott's website.[12] Total sales for each industry are obtained from the ASM. A higher import penetration implies that a larger share of an industry's U.S. sales is accounted for by imports from China, 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

$$\Delta \ln(p_{it}) = \beta_0 \Delta \ln(w_{it}) + \beta_1 \Delta \ln(w_{it}) * IP_{it}^{CN} + \alpha IP_{it}^{CN} + \gamma X_{it} + \rho_t + \epsilon_{it}, \tag{21}$$

where IP_{it}^{CN} is industry i's import penetration from China in year t.[13]

The first column of Table 4 presents the results from this regression. We find that higher import penetration significantly lowers pass-through in a given industry. While an industry with no imports from China exhibits a pass-through from wages to prices of about 2.5%, pass-through would be cut in half in an industry in which the share of sales originating from China is 10%. 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 from China exhibit relatively lower pass-through.

In column (2), we estimate a similar specification where instead of interacting the wage change with the level of import penetration we use its change since 1997, similar to the measure in Autor et al. (2013). The result is relatively similar to before: an industry that experienced a 10 percentage point increase in import penetration from China since 1997 exhibits pass-through of wages to prices that is about 1.1 percentage points lower than an industry with no Chinese imports.

As an alternative, we next construct a dummy variable for whether in a given year an industry's import penetration is above the 75th percentile of import penetration across all industries in that year. We also construct the complementary dummy for industries below the 75th percentile. Since the cut-off is recomputed in each year, the set of industries where a given dummy is equal to one changes from year to year. The point estimate in column (3) of Table 4 shows that industries with a high level of import penetration exhibit a pass-through from wages to prices that is lower than the pass-through in industries with low import penetration. However, the effect is statistically insignificant. In column (4), we instead choose as cutoff the 90*th* percentile of import penetration. We find that industries with import penetration from China below the 90th percentile in a given year exhibit significantly positive

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

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

Table 4: Pass-Through Regressions and Import Penetration

	(1)	(2)	(3)	(4)	(5)	(6)
			Within Year		Across Years	
	IP	Δ IP	75th Pct	90th Pct	75th Pct	90th Pct
Δ Wage	0.0247*	0.0245*				
	(0.0139)	(0.0137)				
Δ Wage × IP	-0.128*	-0.115*				
	(0.0662)	(0.0658)				
Δ TFP	-0.169***	-0.170***	-0.171***	-0.170***	-0.168***	-0.170***
	(0.0196)	(0.0196)	(0.0196)	(0.0195)	(0.0196)	(0.0195)
Δ Wage × Low IP			0.0228	0.0231*	0.0289**	0.0242*
			(0.0144)	(0.0137)	(0.0144)	(0.0136)
Δ Wage × High IP			0.0132	-0.0430*	-0.0527**	-0.0750***
			(0.0214)	(0.0220)	(0.0259)	(0.0258)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.0375	0.0382	0.0376	0.0374	0.0386	0.0377
Observations	12398	12305	12398	12398	12398	12398

IP refers to import penetration. Driscoll-Kraay standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

pass-through, while pass-through is in fact negative in industries with high competition from China.

In Columns (5) and (6) of Table 4, we instead use the 75th percentile and the 90th percentile of import penetration from China across all years as cutoff. This regression analyzes whether pass-through is lower for an industry once it crosses a fixed threshold level of import penetration. Since import penetration rises over time, more industries are classified as having a large import penetration in later years than in earlier years. The regression indicates again that industries with low import penetration exhibit significantly higher pass-through from wages to prices while industries with high import penetration do not.

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 lower increase in price inflation. As import penetration has risen significantly over the last decades, pass-through in manufacturing overall has declined.

Table 5: Different Measures of Concentration Measures in 1995 and 2012

	1995	2012
Top-4 Sales Share	33.2%	36.6%
Top-20 Sales Share	59.9%	63.6%
Sales HHI	0.052	0.065
Top-4 Employment Share	27.6%	27.1%
Top-20 Employment Share	49.5%	48.6%
Employment HHI	0.045	0.046

Sales concentration is for 1997, the earliest year available from the Census Bureau on a NAICS basis. Employment concentration is from the NETS database.

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 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.[14] 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, respectively, and the HHI of the 50 largest firms. All three of these measures are obtained from the Census of Manufacturing in 1997, 2002, 2007, and 2012, and linearly interpolated in between census years.[15] 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.[16] 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 1995 to 2012. The increase is more pronounced for sales-based measures as discussed in Hershbein et al. (2018).

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

[15] 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

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

Table 6: Pass-Through and Concentration in Manufacturing (1993-2016)

	(1)	(2)	(3)	(4)	(5)	(6)
		Sales			Employment	
	Top-4	Top-20	HHI	Top-4	Top-20	HHI
Δ Wage	0.143***	0.177***	0.114***	0.119***	0.132***	0.0613***
	(0.0347)	(0.0574)	(0.0279)	(0.0321)	(0.0396)	(0.0199)
Δ Wage × SC 4	-0.205***					
	(0.0566)					
Δ TFP	-0.181***	-0.182***	-0.182***	-0.171***	-0.172***	-0.168***
	(0.0205)	(0.0204)	(0.0211)	(0.0197)	(0.0196)	(0.0195)
Δ Wage × SC 20		-0.185**				
		(0.0762)				
Δ Wage × Sales HHI			-0.690***			
			(0.233)			
Δ Wage × EC 4				-0.213***		
				(0.0773)		
Δ Wage × EC 20					-0.159**	
					(0.0631)	
Δ Wage × Emp HHI						-0.305
						(0.190)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.0626	0.0588	0.0623	0.0433	0.0424	0.0418
Observations	8705	8705	8585	11741	11741	11741

SC refers to sales concentration. Driscoll-Kraay standard errors in parentheses.
SC 4 (EC 4) is the sales (employment) share of the top 4 firms.
SC20 and EC 20 are defined analogously
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We estimate the equation

$$\Delta \ln(p_{it}) = \beta_0 \Delta \ln(w_{it}) + \beta_1 \Delta \ln(w_{it}) * C_{it} + \alpha C_{it} + \gamma X_{it} + \delta_i + \rho_t + \epsilon_{it}, \tag{22}$$

where C_{it} is the measure of concentration used. We report the results in Table 6 using different measures of market concentration. 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 0.14% 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 0.04%. 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.

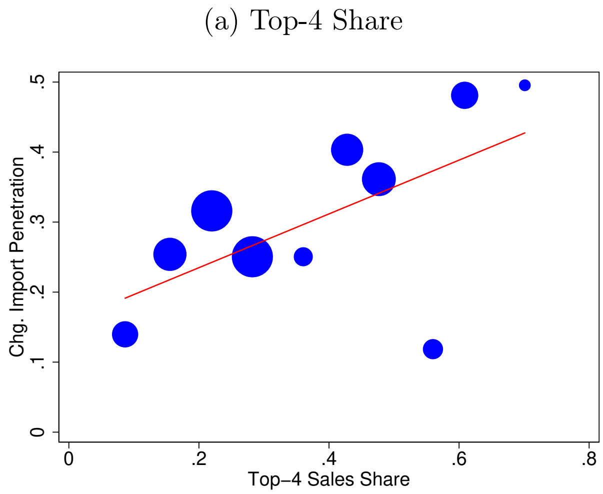
Equation (15) from our theoretical framework is key to understand the intuition of why market concentration can also lead to lower pass-through. When firms set high markups, they are able to at least partially absorb cost-push shocks into their markup without passing through the rising costs to consumers. 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.

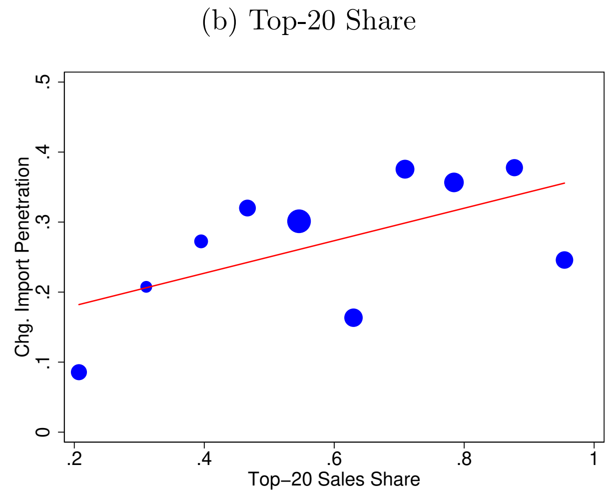
4.3 Import Penetration versus Market Concentration

While our theoretical and empirical analyses provide strong support for rising import penetration and increasing market concentration as sources of declining pass-through, we not identify the relative quantitative importance of these two channels. In this subsection we document that they are positively correlated across industries. In related work, Amiti and Heise (2020) study how import penetration and market concentration affect markups. They argue that the increase in import penetration and market concentration reflects the same underlying mechanism.

Figures 8a and 8b show that import penetration and concentration are in fact closely related. In these figures, we sort all industries by their average market concentration over the period 1997-2012, and assign them to equally spaced buckets. We then take the average of the increase in total import penetration from all countries between 1997 and 2012 across all industries in the bucket. 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 Manufacturing. The figure highlights a strong positive relationship between market concentration and the growth in overall import penetration between 1997 and 2012. Industries with a high average concentration also exhibit a strong increase in import competition. Figures A.10a and A.10b in Appendix B plot similar figures for import

Figure 8: Import Penetration versus Market Concentration





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 reflecting the same mechanism, and provides further evidence in support of our Theorem 3.1. As foreign exporters entered U.S. markets and raised import penetration, many domestic firms exited, increasing U.S. domestic concentration, as documented by Gutiérrez and Philippon (2017). 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 Figure A.6 in Appendix C for Canada, Figure A.7 for the UK, and Figure A.8 for the Euro zone, respectively. Since these countries have also been experiencing rising import competition and increase in 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 after the most recent recessions 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 (2020) argue that the rise in import penetration and market concentration reflect the same underlying mechanism.

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), 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 Theory

A.1 Detailed Derivations

A.1.1 Cost Function

The firm's production function is

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

The firm's cost function is

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

where w and r are the cost of labor and capital, respectively, taken as given by the firm. Minimization of the cost function (24) subject to the production function (23) implies

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

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

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

Thus, the cost function is

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

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.

A.1.2 Market Structure and Demand Elasticity

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

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

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

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

We now define firms' market share as

$$\varphi_s(k,i) = \frac{p_s(k,i)y_s(k,i)}{\sum_{i'} p_s(k,i')y_s(k,i')} = \frac{p_s(k,i)^{1-\eta}}{\sum_{i'} p_s(k,i')^{1-\eta}} = \frac{p_s(k,i)^{1-\eta}}{p_s(k)^{1-\eta}}. \tag{32}$$

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

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

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

A.1.3 Price Setting

The firm's profit maximization problem

$$\max_p \left[p_s(k,i) - c_s(k,i)\right]\left(\frac{p_s(k,i)}{p_s(k)}\right)^{-\eta}\left(\frac{p_s(k)}{P_s}\right)^{-\sigma} Y_s \tag{34}$$

leads to the first-order condition

$$\begin{aligned}&\left[(1-\eta)p_s(k,i)^{-\eta} + \eta p_s(k,i)^{-\eta-1}c_s(k,i)\right] p(k)^{\eta-\sigma}P_s^{\sigma}Y_s \\ &+\left[(\eta-\sigma)p_s(k,i)^{-\eta}p_s(k)^{\eta-\sigma-1}P_s^{\sigma}Y_s\frac{dp_s(k)}{dp_s(k,i)}\right]\left[p_s(k,i)-c_s(k,i)\right] = 0.\end{aligned} \tag{35}$$

Substituting in the derivative of the price index,

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

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

$$p_s(k,i) = \frac{\eta - (\eta-\sigma)\varphi_s(k,i)}{(\eta-1)-(\eta-\sigma)\varphi_s(k,i)}c_s(k,i). \tag{37}$$

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

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

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

A.1.4 Pass-Through

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

$$\begin{aligned} d\log p_s(k,i) &= d\log \mathcal{M}_s(k,i) + d\log c_s(k,i) \\ &= d\log \mathcal{M}_s(k,i) - d\log A + \alpha d\log w_i + (1-\alpha) d\log r. \end{aligned} \tag{39}$$

The change in the markup is given by

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

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

$$d\log p_s(k,i) = -\Gamma_s(k,i)\left[d\log p_s(k,i) - d\log p_s(k)\right] - d\log A + \alpha d\log w_i + (1-\alpha) d\log r. \tag{41}$$

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

$$d\log p_s(k,i) = \frac{\Gamma_s(k,i)}{1+\Gamma_s(k,i)} d\log p_s(k) - \frac{1}{1+\Gamma_s(k,i)} d\log A + \frac{\alpha}{1+\Gamma_s(k,i)} d\log w_i, \tag{42}$$

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

Finally, the derivative of the markup elasticity with respect to the market share $\varphi_s(k,i)$

is given by

$$\frac{d\Gamma_s(k,i)}{d\varphi_s(k,i)} = \frac{\left[\frac{\eta}{\eta-\sigma} - \varphi_s(k,i)\right]\left[1 - \frac{\eta-\sigma}{\eta-1}\varphi_s(k,i)\right] + \left[1 - \frac{\eta-\sigma}{\eta-1}\varphi_s(k,i)\right] + \frac{\eta-\sigma}{\eta-1}\left[\frac{\eta}{\eta-\sigma} - \varphi_s(k,i)\right]}{\left\{\left[\frac{\eta}{\eta-\sigma} - \varphi_s(k,i)\right]\left[1 - \frac{\eta-\sigma}{\eta-1}\varphi_s(k,i)\right]\right\}^2} > 0. \tag{43}$$

A.2 Proof of Theorem

Part 1: From the definition of $\Gamma_s(k,i)$, if firms have positive market share then $\Gamma_s(k,i) > 0$. From the pass-through equation (15), firms' change in price is then a combination of the change in the industry's price index $p_s(k)$ and their own wage cost shock. From the definition of an industry's price index $p_s(k) = (\sum_i p_s(k,i)^{1-\eta})^{1/(1-\eta)}$, we have that

$$\frac{\partial \log p_s(k)}{\partial \log p_s(k,i)} = \frac{p_s(k,i)^{1-\eta}}{\sum_i p_s(k,i)^{1-\eta}} = \varphi_s(k,i). \tag{44}$$

Thus, a firm's effect on the industry's price index is equal to the firm's market share. With symmetric firms, each firm's effect is equal to $1/N_s(k)$.

Since by assumption there are both domestic and foreign firms in the industry and foreign firms are unaffected by domestic wage shocks, it follows that the change in the industry's price index is less than the wage effect,

$$d \log p_s(k) < \alpha d \log w_i. \tag{45}$$

From the pass-through equation (15), the affected firms therefore change their price by

$$d \log p_s(k,i) = \frac{\Gamma_s(k,i)}{1+\Gamma_s(k,i)} d \log p_s(k) + \frac{\alpha}{1+\Gamma_s(k,i)} d \log w_i < \frac{\alpha(1+\Gamma_s(k,i))}{1+\Gamma_s(k,i)} d \log w_i, \tag{46}$$

and thus pass-through is less than α.

For the second part of the claim, note that as N increases, firms' market shares decline by the assumption of symmetric market shares. Since, as shown by (43), $d\Gamma_s(k,i)/d\varphi_s(k,i) > 0$, a reduction in market share lowers $\Gamma_s(k,i)$. From the pass-through equation (15), pass-through rises since firms put a higher weight on the direct cost shock and a lower weight on the industry price index. As $N \to \infty$, $\Gamma_s(k,i) \to 0$ and pass-through converges to α.

Part 2:

From the pass-through equation (15), firms' change in price is a combination of the change in the industry's price index $p_s(k)$ and their own wage cost shock. As $N_{D,s}(k)/N_s(k)$

declines, the change in the industry's price index due to the wage change becomes smaller and smaller, since fewer firms are subject to the shock and all firms are symmetric. Therefore, pass-through of each firm falls. In the limit, as the industry consists only of foreign firms, $d \log p_s(k) = 0$ and pass-through converges to $\alpha/(1 + \Gamma_s(k, i))$.

B Data Description

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 1980s, 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 obtain all available 5-digit series and fill in missing observations using linear interpolation if data are missing for fewer than three consecutive months. We do not impute values when data for an industry are missing for three or more consecutive months.

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 referring to the same industry when the industry's code changes, and combine disaggregated codes into one if a given 5-digit code can be written forward or backward from more disaggregated 6-digit codes. This aggregation is performed by taking a weighted average over the changes in the industry-level PPI series involved, using total shipments from the Economic Census in 2002 as weight. 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, since these series fluctuate significantly based on the oil price.

For wages, we obtain weekly average earnings data from the Quarterly Census of Employment and Wages (QCEW) from the BLS. The QCEW reports the number of establishments, monthly 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. We use national-level data by 5-digit NAICS industry, and use the weekly average wage of each quarter for our analyses. For most industries, the data cover the period from 1990 to 2018. We create time-consistent NAICS codes using the same mapping as before and seasonally adjust the data.

We merge into our baseline dataset information on industry productivity, using estimates of multifactor productivity (MFP) from the BLS. For the manufacturing sector, the BLS provides annual MFP estimates at the four 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 non-manufacturing industries, the BLS does not provide productivity estimates with the same level of granularity. For these industries, we therefore use MFP measures at the two or three digit NAICS level from the Integrated Industry-Level Production Account (KLEMS) tables provided by the BLS, and use for each industry the productivity value at the next available higher level of aggregation. 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.

We construct several additional controls. We obtain quarterly employment by gender, education, and age from the Quarterly Workforce Indicators (QWI) at the four digit NAICS and three digit NAICS levels from 1990 to 2018. For each industry and quarter, we compute the share of male and female workers, as well as the share of high-skilled and medium-skilled workers, defined by those who have a Bachelor's degree or higher, and those who have a high school or equivalent degree (no college), respectively. 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 the finest level of aggregation available.

C Additional Figures

C.1 Alternative Measures of Recovery

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

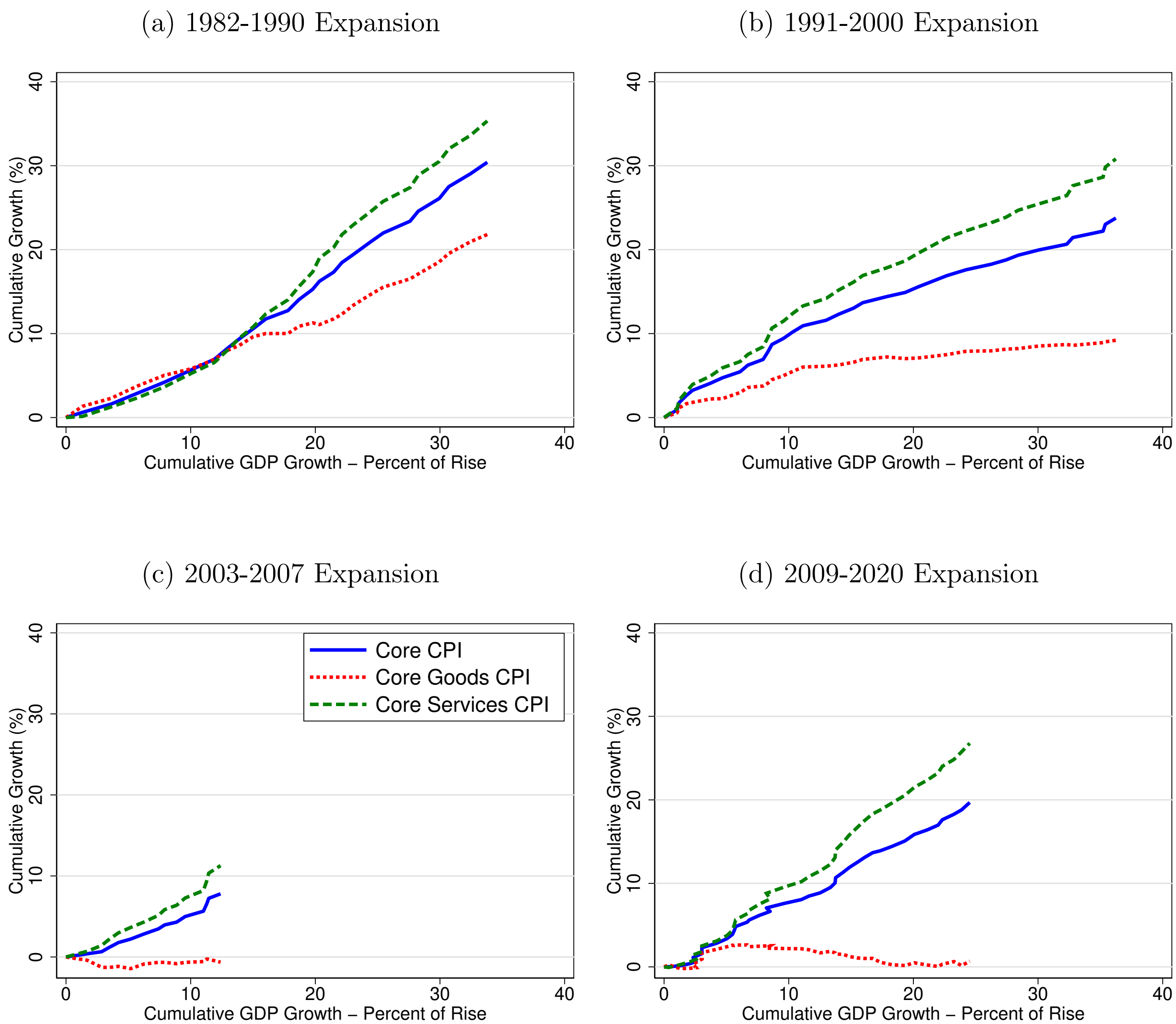
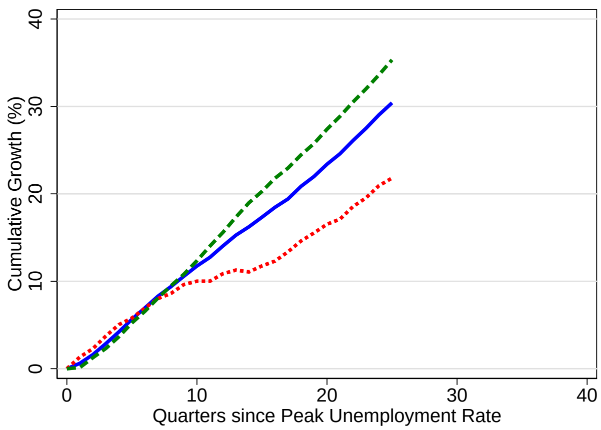
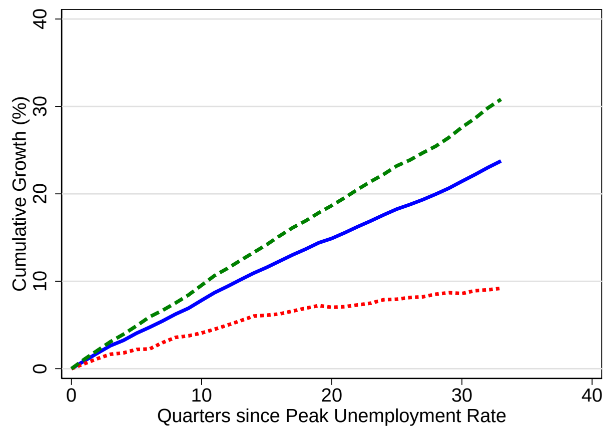


Figure A.2: Inflation from Four Previous Recessions

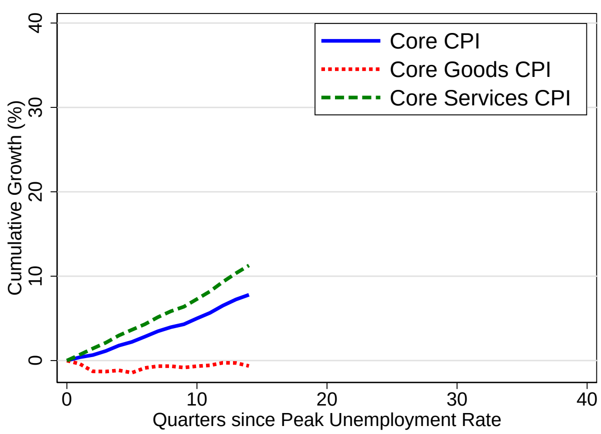
(a) 1982-1990 Expansion



(b) 1991-2000 Expansion



(c) 2003-2007 Expansion



(d) 2009-2020 Expansion

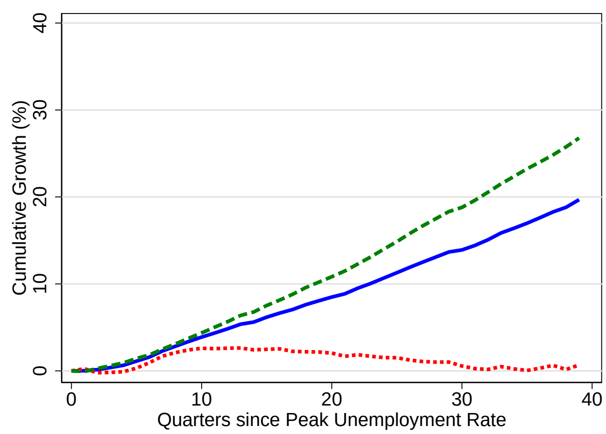
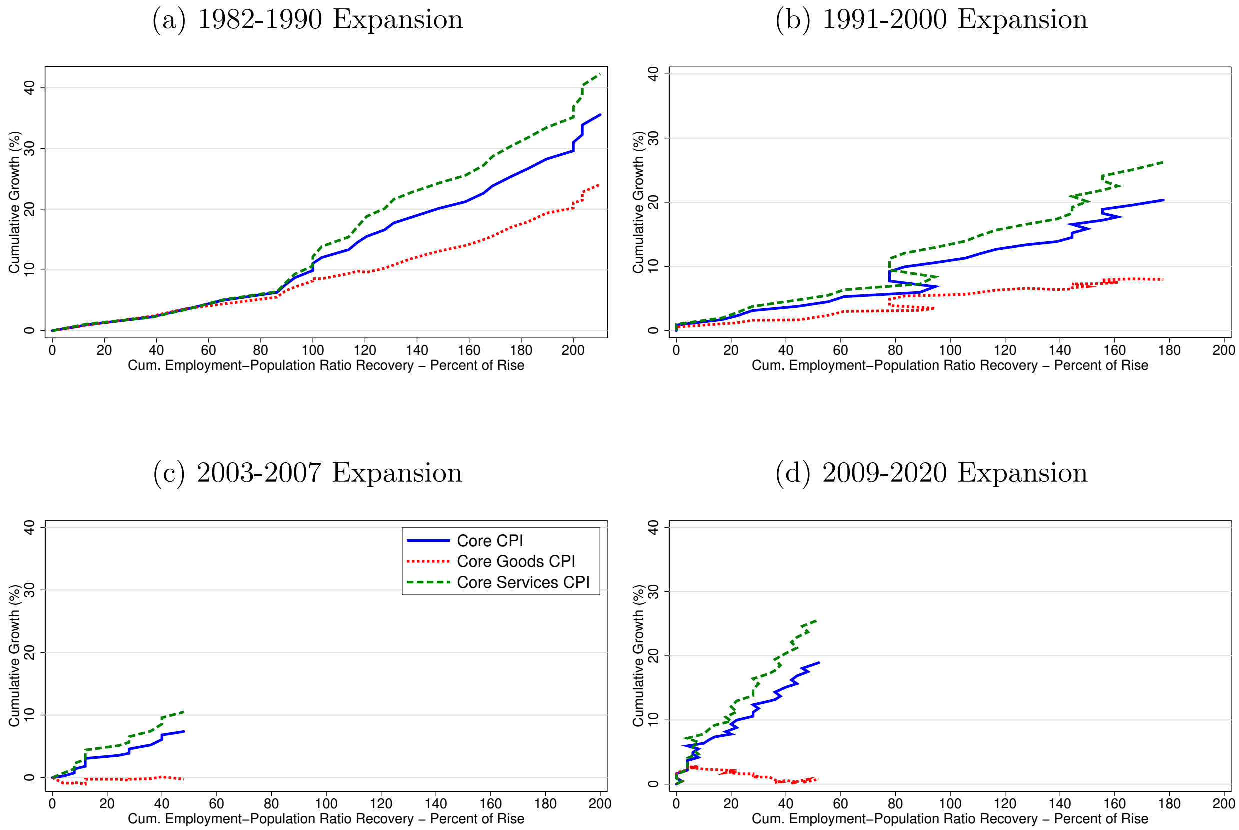


Figure A.3: Inflation versus Employment-to-Population Ratio from Four Previous Recessions



(a) 1982-1990 Expansion

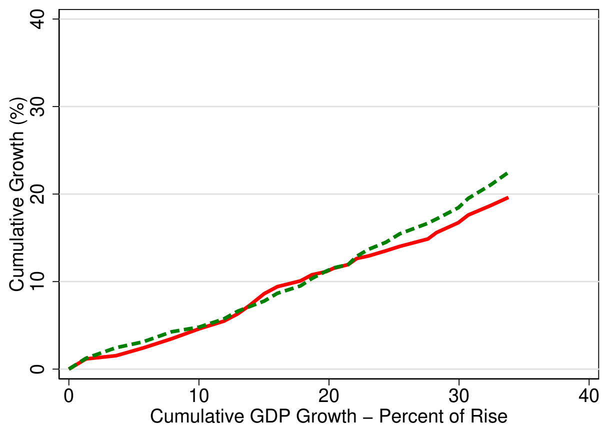
(b) 1991-2000 Expansion

(c) 2003-2007 Expansion

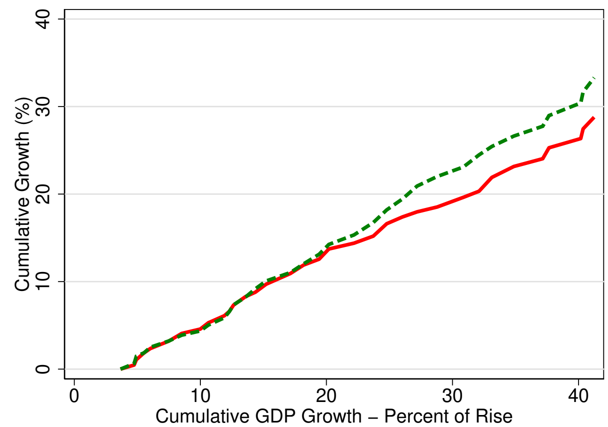
(d) 2009-2020 Expansion

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

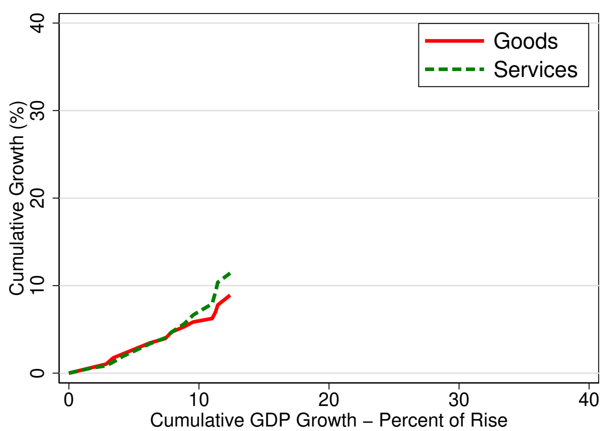
(a) 1982-1990 Expansion



(b) 1991-2000 Expansion



(c) 2003-2007 Expansion



(d) 2009-2020 Expansion

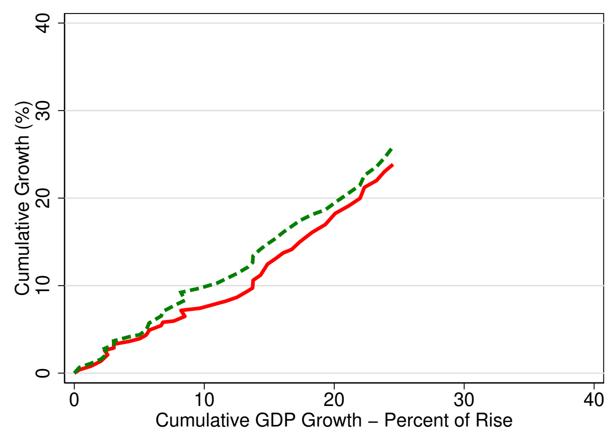
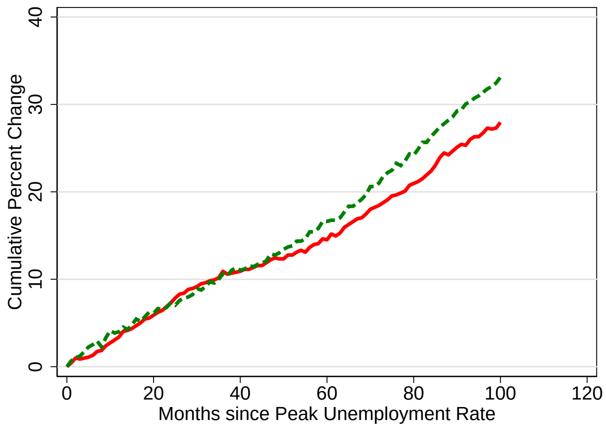
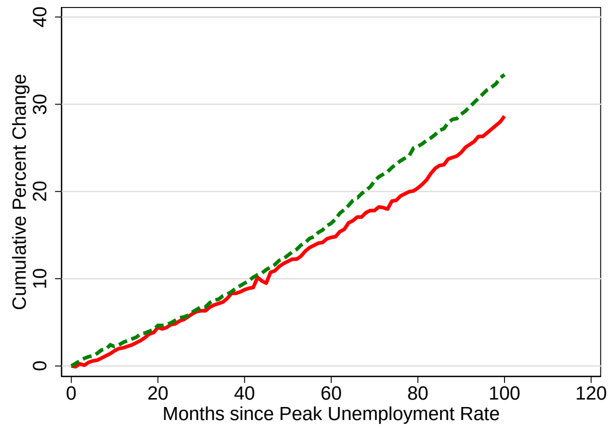


Figure A.5: Wage Growth from Four Previous Recessions

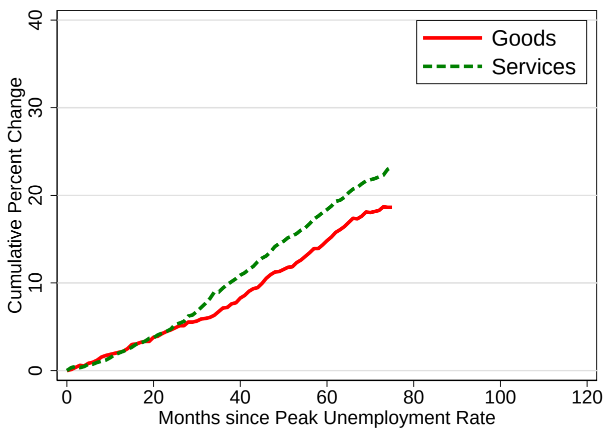
(a) 1982-1990 Expansion



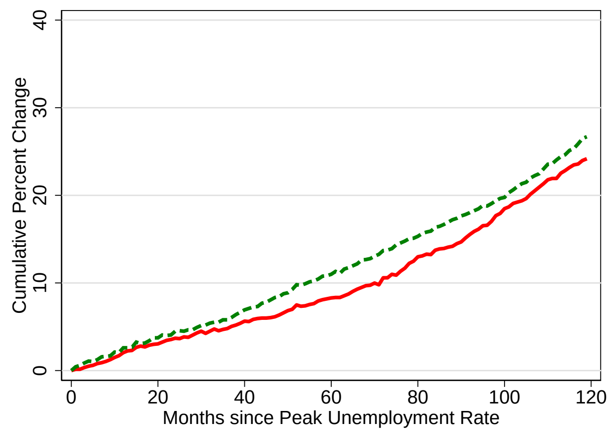
(b) 1991-2000 Expansion



(c) 2003-2007 Expansion



(d) 2009-2020 Expansion

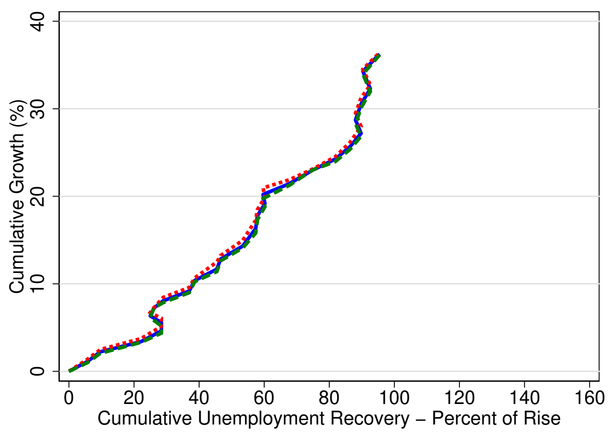


C.2 International Evidence

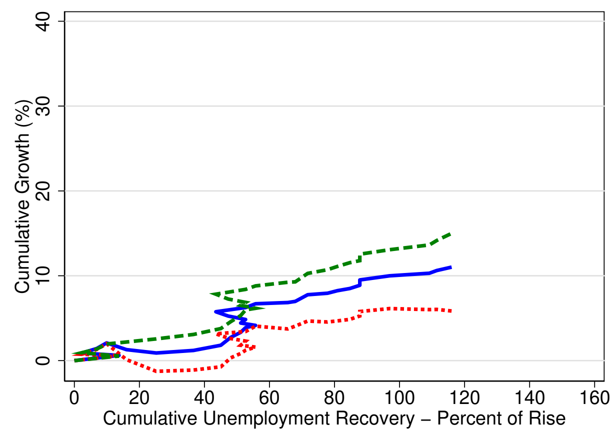
C.2.1 Canada

Figure A.6: Inflation versus Unemployment Recovery from Four Previous Recessions

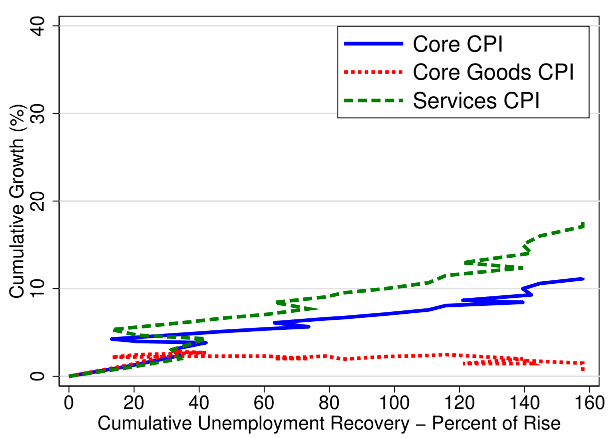
(a) 1982-1990 Expansion



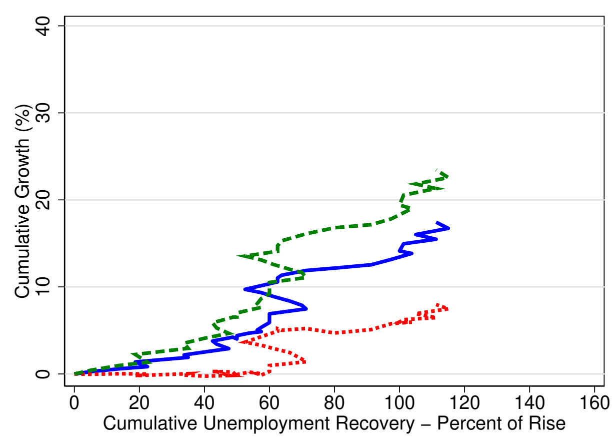
(b) 1991-2000 Expansion



(c) 2003-2007 Expansion



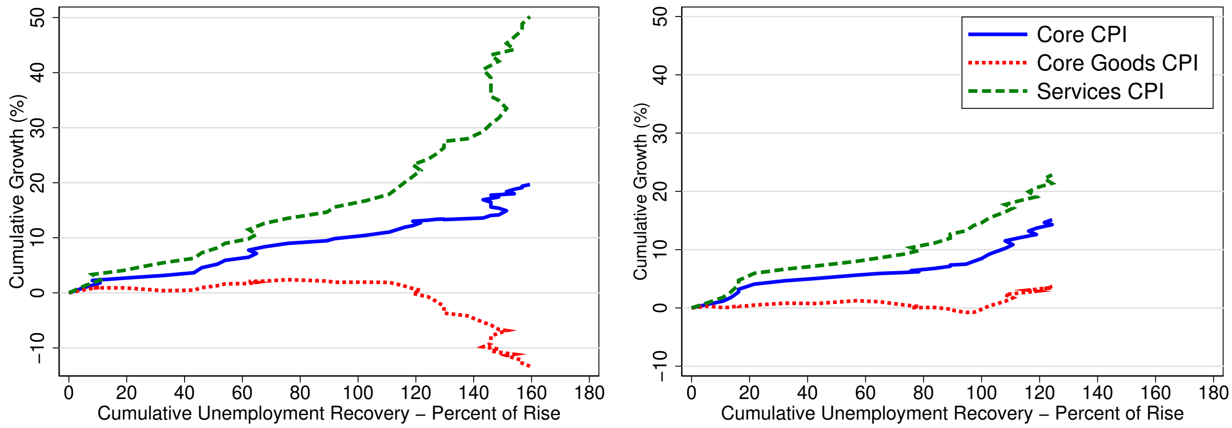
(d) 2009-2020 Expansion



C.2.2 United Kingdom

Figure A.7: Inflation versus Unemployment Recovery from Two Previous Recessions

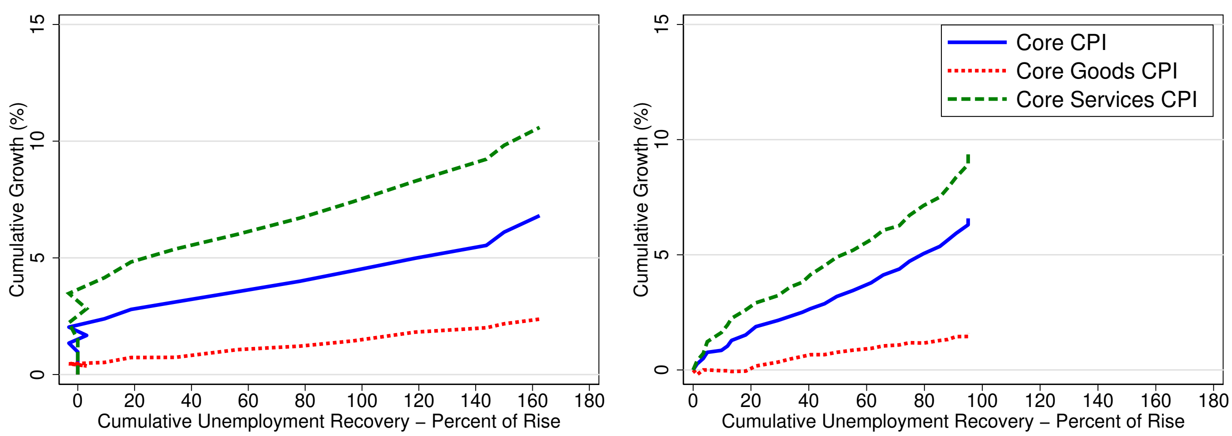
(a) 1993-2000 Expansion (b) 2011-2020 Expansion



C.2.3 Eurozone

Figure A.8: Inflation versus Unemployment Recovery from Two Previous Recessions

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



C.3 Other figures

Figure A.9: Trends in Manufacturing

(a) Top-4 Share (b) HHI

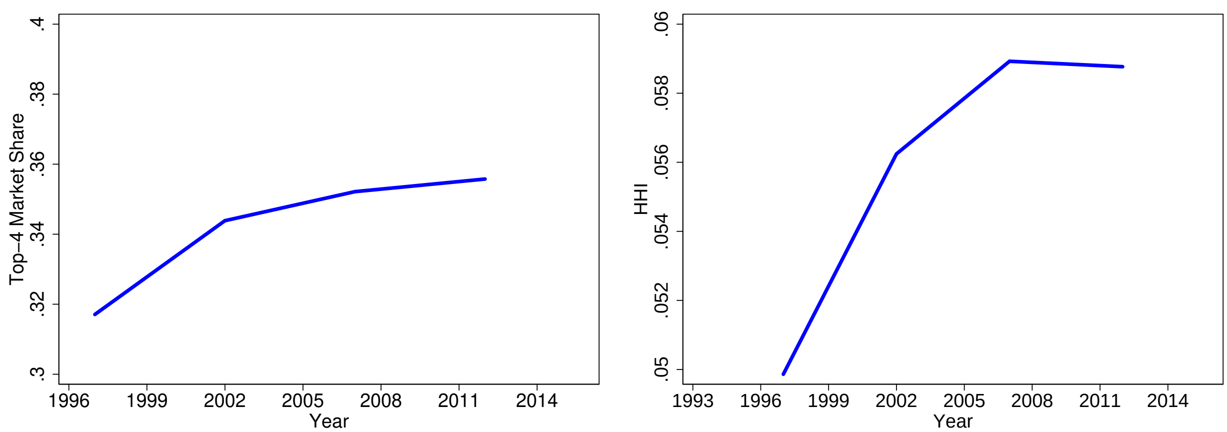
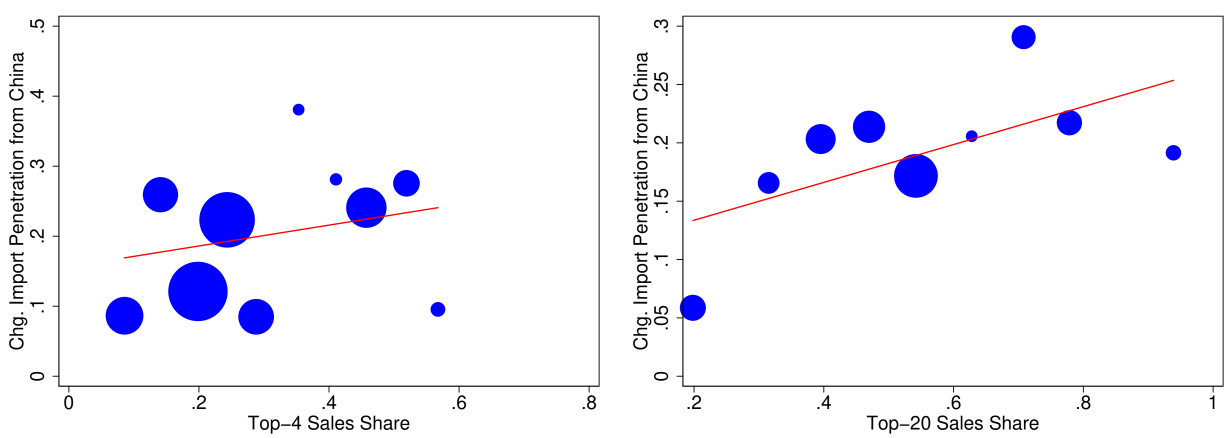


Figure A.10: Market Concentration versus Import Penetration from China

(a) Top-4 Share (b) Top-20 Share



Note: Figures consider only industries with increasing exposure to China reflected in an increase in import penetration from China of at least 3%.

D Additional Tables

Table A.1: Pass-Through Regressions for Goods versus Services, Unweighted Regressions

	(1) Aggregate	(2) No TFP	(3) With TFP	(4) Aggregate	(5) No TFP	(6) With TFP
Δ Wage	0.0314***					
	(0.00865)					
Δ Wage Manuf		0.00665	0.0123			
		(0.00979)	(0.0103)			
Δ Wage Services		0.0847***	0.0750***			
		(0.0229)	(0.0207)			
Δ TFP			-0.0727***			-0.0714***
			(0.0129)			(0.0130)
Δ Wage $\times$ LS				0.133**		
				(0.0529)		
Δ Wage $\times$ LS Manuf					-0.0485	-0.00525
					(0.0477)	(0.0480)
Δ Wage $\times$ LS Services					0.257***	0.218***
					(0.0883)	(0.0775)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.00424	0.00621	0.0133	0.00464	0.00580	0.0127
Observations	12999	12999	12999	12782	12782	12782

TFP is total factor productivity. LS refers to the labor share. Driscoll-Kraay standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Pass-Through Regressions for Goods versus Services with Different Fixed Effects

	(1) Time FE	(2) Industry FE	(3) No FE	(4) Time FE	(5) Industry FE	(6) No FE
Δ Wage Manuf	0.0221	0.0401	0.0631**			
	(0.0220)	(0.0242)	(0.0267)			
Δ Wage Services	0.0687**	0.111***	0.105***			
	(0.0304)	(0.0283)	(0.0269)			
Δ TFP	-0.0912***	-0.0831***	-0.0982***	-0.0910***	-0.0829***	-0.0950***
	(0.0158)	(0.0122)	(0.0142)	(0.0161)	(0.0130)	(0.0139)
Δ Wage × LS Manuf				-0.0992	0.280	0.296
				(0.139)	(0.191)	(0.195)
Δ Wage × LS Services				0.191*	0.312***	0.365***
				(0.100)	(0.0986)	(0.0970)
Constant			-0.0179			-0.00965
			(0.0264)			(0.0299)
Time Fixed Effects	Yes	No	No	Yes	No	No
Industry Fixed Effects	No	Yes	No	No	Yes	No
R2	0.0287	0.0588	0.0503	0.0289	0.0563	0.0483
Observations	12727	12727	12727	12727	12727	12727

TFP is total factor productivity. LS refers to the labor share. Driscoll-Kraay standard errors in parentheses. All regressions are weighted by an industry's total sales in 2012.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$