Robot Adoption and Inflation Dynamics*

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Abstract

We leverage variation in robot adoption across U.S. metropolitan areas to document that automation reduces the sensitivity of inflation to unemployment. A New Keynesian model with search frictions and automation rationalizes our empirical findings through two mechanisms. First, automation shrinks workers' bargaining power, dampening the sensitivity of wages to unemployment. Second, automation reduces the labor share, muting the pass-through from wages into prices. Both channels flatten the price Phillips curve. However, when boosting automation is costly, the threat of robot adoption is no longer effective in curtailing workers' bargaining power amidst large expansionary shocks, leading to a steep Phillips curve.

Key Words: Automation, robots, inflation, Phillips curve, unemployment.

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1 Introduction

Over the past few decades, advanced economies have witnessed a substantial increase in the use of robots and other forms of automation in production processes. This phenomenon has generated comprehensive implications for the labor market, contributing to the polarization of employment opportunities and the decline of middle-skilled jobs, as well as compressing wages at the lower end of the earnings distribution (Acemoglu and Restrepo, 2018, 2020a, 2020b, 2022; Graetz and Michaels, 2018; Acemoglu et al., 2020). However, notwithstanding the key role that labor market conditions have on wage and price setting, little is known about how robot adoption may influence inflation dynamics. In this paper, we show empirically, theoretically, and quantitatively that the surge in automation could explain the muted sensitivity of inflation to unemployment observed in advanced economies until the Covid pandemic.

We start by providing novel empirical evidence showing that robot adoption alters both price and wage inflation. To do so, we build a panel of non-tradable goods inflation, wage inflation, unemployment rate and robot adoption at the U.S. metropolitan area (MSA) level. To measure automation, we follow Acemoglu and Restrepo (2020a) and combine the robot installation for each industry at the U.S. national level with the employment share of each industry at the MSA level. In this way, we measure the robot installed per employee for each metropolitan area. We end up with a panel across 384 MSAs at the annual frequency from 2008 and 2018. While 2008 is the first year for which the U.S. Bureau of Economic Analysis provides price information across MSAs, our sample period tracks the years in which the surge of automation took place.

Our empirical approach closely follows that of Hazell et al. (2022), which we extend to incorporate the role of automation on inflation dynamics. Specifically, we regress both non-tradable goods inflation and wage inflation on the lagged values of the unemployment rate and its interaction with robot adoption, while controlling in isolation for the role of robot adoption and the non-tradable goods relative price. Hazell et al. (2022) show that the estimated sensitivity of inflation to unemployment maps into the slope of the aggregate price Phillips curve implied by a multi-region model. This setting allows us to saturate the regression with year fixed effects, which not only control for supply shocks and inflation expectations that are common across areas, but most importantly absorb the endogenous response of monetary policy to common demand shocks (Beraja et al., 2019; McLeay and Tenreyro, 2020; Fitzgerald et al., 2023).

However, this cross-sectional analysis of inflation dynamics would not suffice to uncover the Phillips curve if local idiosyncratic supply shocks are correlated with changes in local labor markets. To purge the variation of unemployment from idiosyncratic supply shocks, we follow Hazell et al. (2022) and instrument the unemployment rate with local tradable demand spillovers. In particular, we build a shift-share instrument that weights the log difference of value added of tradable industries at the national level with the value-added share of each tradable industry in each metropolitan area. Then, to uncover the causal effect of automation, we instrument robot adoption with a variable that replaces the robot installation across industries observed in the U.S. with those of the five largest European economy, as in Acemoglu and Restrepo (2020a). Under the identifying restriction that robot demand shocks are weakly correlated across advanced countries, our instrumenting strategy isolates the supply-side component which caused the surge in the efficiency and widespread usage of robots.

In our baseline results, the interaction of unemployment and robot adoption is positive and highly statistically significant, indicating a significant role of automation in decoupling inflation and unemployment. This effect is also economically relevant: an increase in robot adoption by one standard deviation reduces the sensitivity of prince inflation and wage inflation to unemployment by 17% and 9%, respectively. This differential magnitude suggests that that robot adoption also diminishes the influence of wage changes onto price changes. Overall, our empirical analysis uncovers three novel findings relating automation to inflation dynamics: robot adoption reduces (*i*) the sensitivity of price inflation to unemployment, (*ii*) the sensitivity of wage inflation to unemployment, and (*iii*) the pass-through from wages into prices.

Our empirical findings keep holding in a comprehensive battery of robustness checks that validate the role of automation in decoupling the movements of inflation and unemployment above and beyond potential alternative explanations and confounding factors. For instance, the role of robot adoption in dampening the sensitivity of non-tradable goods inflation to the unemployment rate is highly statistically significant even when controlling the role of the time-varying differences across MSAs in the age structure of the population (Aksoy et al., 2019; Basso and Jimeno, 2021; Acemoglu and Restrepo, 2022), the labor market participation of workers with different gender, race, and education, differences in the average marginal propensity to consume (Herreño and Pedemonte, 2022), the relevance of abstract, routine, manual, and offshorable occupations (Autor et al., 2013; Siena and Zago, 2022), as well as the exposure of metropolitan areas to foreign import competition (Forbes, 2019; Heise et al., 2022, 2023).

To rationalize our empirical evidence on how automation alters inflation dynamics, we extend an otherwise standard New Keynesian model with two key features: the possibility of robot adoption, in the spirit of Acemoglu and Restrepo (2020a), and search frictions in the labor market. The economy features a representative household consisting of a continuum of workers with perfect consumption insurance, who directly search for a job. The production sector has three layers: (*i*) a varying measure of producers that operate using either robots or workers, and post vacancies in the labor market, (*ii*) a continuum of monopolistically competitive wholesalers that purchase the goods of the producers and transform them into different varieties, subject to a price setting friction in the form of Rotemberg costs, and (*iii*) a representative retailer that aggregates the different varieties into the final good. In addition, machine manufacturers transform final goods into machines with a linear technology featuring robot-specific technological change. Accordingly, the relative price of robots declines with the level of technological change. The economy is closed by a standard Taylor rule that sets the nominal interest rate.

Automation is modulated by producers' decision to use either workers or machines. Producers trade off the certainty of installing and operating with a robot with the uncertainty of possibly hiring a worker but — conditional on that — operating at a relatively higher efficiency. Specifically, upon entry — and after paying a fixed operating cost — producers draw an idiosyncratic efficiency in employing workers, and then decide to use either a labor technology (i.e., labor firms) or a machine technology (i.e., robot firms). Labor firms open vacancies at given posted wage, such that high-efficient firms offer relatively higher wages. Machine firms purchase a robot from machine manufacturers, and produce with certainty.

This setting defines an automation threshold, that is, a level of the efficiency in operating the labor technology that determines whether firms opt to either post a vacancy and look for workers or install a machine. Low-efficiency firms install machines, leading to the replacement of low-wage jobs with robots, in line with the evidence of Acemoglu and Restrepo (2018, 2020b). The automation threshold crucially depends on the job filling probability and the levels of both wages and the price of robots. When wages increase relative to the price of robots, firms may replace workers with machines. In the model, the automation cut-off varies across steady states, as a function of the exogenous level of robot-specific technological change, and around the steady state upon the occurrence of a shock, as a function of the endogenous response of prices.

When characterizing the price Phillips curve, we show that automation — interpreted as a rise in robot-specific technological change — reduces its slope. The flattening effect of automation is due to two main mechanisms. First, automation raises the fraction of firms operating with machines, lowering the labor share in value added. As a result, it mutes the pass-through from wages into prices. Second, the outside option of automating production negatively affects workers' bargaining power, dampening the responsiveness of wages to the unemployment gap.

In the quantitative analysis, we consider two steady states that differ uniquely in the level of robot-specific technological change. We calibrate the first economy to target the 0.2% robot-per-employee ratio of the U.S. in the 2000s, whereas the second economy features a degree of automation three times as large, which replicates the standard deviation of robot penetration across MSAs in the data. We find that positive demand shocks — lowering the unemployment gap by the same amount in the two steady states — reduce the responsiveness of price inflation and wage inflation in the high-automation economy by 14% and 13%, respectively. Thus, the model accounts for 82% of the drop in the slope of the price Phillips curve estimated in the data, while overestimating the flattening of the wage Phillips curve (13% vs. 9% in the data). As such, our economy understates the drop in the wage-to-price pass-through. However, we show how to extend the model so that to generate an empirically relevant reduction in the pass-through.

Our model can rationalize not only the muted inflation sensitivity to unemployment in the pre-Covid period, but also the sudden resurgence of a steep Phillips curve. When ramping up automation is costly and machine manufacturers face adjustment costs, the threat that robots pose to workers' bargaining power crucially depend on the size of the shock realizations. When facing a small expansionary shock, firms can purchase additional machines without facing a sharp increase in robot prices, and thus gain an upper hand on wage negotiations. In this case, both the wage and price Phillips curves are flat. However, when the size of an expansionary shock is substantial, installing all the required robots to meet demand would be increasingly costly, forcing producers to continue to operate using labor. Consequently, the threat of robot adoption is no longer effective in curtailing workers' bargaining power, and wages strongly react to changes in the unemployment gap. In other words, robot adoption alters the price Phillips curve such that it flattens when the size of shocks is small, but can quickly steepen up amidst large shock realizations.

Our work relates to the literature on inflation dynamics in the post 1980s, suggestive of a flat Phillips curve (Blanchard, 2016; Stock and Watson, 2020; Del Negro et al., 2020). This evidence may be due to policy improvements and better anchoring of expectations (Ball and Mazumder, 2011; McLeay and Tenreyro, 2020; Hazell et al., 2022; Bergholt et al., 2023), labor market changes muting the responsiveness of wages (Stansbury and Summers, 2020; Siena and Zago, 2022; Faccini and Melosi, 2023), globalization (Forbes, 2019; Heise et al., 2022), changes in the shocks composition (Gordon, 2013; Coibion and Gorodnichenko, 2015), changes in firm inter-linkages (Galesi and Rachedi, 2019; Höynck, 2020; Rubbo, 2023), financial frictions (Gilchrist et al., 2017), and a non-linear Phillips curve (Harding et al., 2022a). We emphasize that automation can account for the muted inflation sensitivity to the unemployment rate in the pre-Covid period, while also rationalizing a steep Phillips curve amidst large expansionary shocks.

The two closest papers to ours are Fornaro and Wolf (2021) and Leduc and Liu (2023). Fornaro and Wolf (2021) build a model with sticky prices and robot adoption to show that monetary policy accommodations can reconcile a spike of automation with limited effect on employment and inflation in medium and long run. We take a complementary approach by emphasizing that robot adoption decouples inflation and labor market dynamics in the short run, taking as given the stance of monetary policy. Leduc and Liu (2023) build a real model with robot adoption and search frictions to account for unemployment fluctuations. While our work share their focus on the threat that robots pose to workers' bargaining power, we look at how automation alters the slope of the Phillips curve.

2 Empirical Evidence

This section provides novel empirical evidence on how robot adoption leads to a decoupling between inflation and unemployment. Specifically, we study a panel of price inflation, wage inflation, unemployment, and robot adoption across U.S. metropolitan areas. To estimate the effect of automation on the relationship between inflation and unemployment, we use the variation across U.S. metropolitan areas in both tradable demand spillovers and robot adoption.

2.1 Data

We build a data set of non-tradable goods inflation, wage inflation, the unemployment rate, and robot adoption across 384 U.S. metropolitan areas at the annual frequency from 2008 to 2018. The frequency and the time period of our panel differ from those of Hazell et al. (2022) and Fitzgerald et al. (2023), as we start much later in time, from the early 2000s on, to capture the period in which automation became more significant.[1]

We use the information on the regional price parities of the U.S. Bureau of Economic Analysis (BEA), which gives a breakdown of prices at the MSA level by providing data on total prices, the price of goods, as well as distinct series for the price of rents, utilities, and other services. We complement it with information on wages, defined as the average compensation per job from the BEA, the unemployment rate from the Local Area Unemployment Statistics of the U.S. Bureau of Labor Statistics (BLS), robot installed at the industry level for the U.S. and the five largest European countries from the International Federation of Robotics, employment at the industry-MSA level from the Quarterly Census of Employment and Wages of the BLS. To derive a measure of robot adoption at the MSA-year level, we follow the two-step procedure of Acemoglu and Restrepo (2020a): we compute the robot per employee for each industry at the U.S. national level, and combine it with the employment share of each industry at the MSA level. In this way, we derive the ratio of installed robots per employee for each MSA-year pair.

Finally, we also consider value added at the industry-MSA level from the BEA, and employment at the industry-country level for the five largest European countries from EUKLEMS.

2.2 Econometric Specification

We estimate the causal effect of robot adoption on the sensitivity of price inflation to unemployment using the following panel regression:

$$\pi_{N,i,t} = \beta\, u_{i,t-1} + \gamma\, u_{i,t-1}\,(m_{i,t-1} - \bar{m}) + \zeta\, m_{i,t-1} + \chi\, p_{N,i,t} + \alpha_i + \delta_t + \epsilon_{i,t}, \quad (1)$$

where $\pi_{N,i,t}$ is the inflation rate of non-tradable goods of MSA i at year t, defined as the log-difference of the price of services excluding rents and utilities, $u_{i,t}$ is the unemployment rate, $m_{i,t}$ denotes robot adoption, $\bar{m} = \sum_i \sum_n \frac{m_{i,t}}{n_i n_t}$ is its average value across all MSA-year observations, where n_i is the number of MSA in the sample and n_t is the number of years, and $p_{N,i,t}$ is the relative price of non-tradable goods. As in Ball and Mazumder (2011), Hazell et al. (2022) and Fitzgerald et al. (2023), we consider the unemployment rate as lagged by

[1] The data on prices at the annual frequency across 384 MSAs start in 2008. Although prices at the metropolitan areas are available also at the quarterly and semi-annual frequency well before than 2008, they only track around 20 MSAs. Consequently, we opt for a panel at the annual frequency from 2008 onwards to focus on the period of more substantial robot adoption while maximizing the cross-sectional dimension of our data.

one year. Similarly, we also lag by one year the robot adoption variable. The regression also includes MSA fixed effects, α_i, and year fixed effects, δ_t.

In this setting, the coefficient β denotes the local sensitivity of non-tradable goods inflation to the unemployment rate for a MSA with an average robot adoption. The parameter γ – associated to our regressor of interest, the interaction between the unemployment rate and the (demeaned) robot-per-employee ratio – captures how the inflation sensitivity to unemployment varies with automation.[2]

We estimate the coefficients β and γ by leveraging cross-sectional differences in unemployment rate, inflation, and robot adoption across metropolitan areas. For instance, the average value of the unemployment rate at the MSA level in our sample equals 6.8%, but it is highly heterogeneously distributed, as it ranges from a value of 3% in Bismarck, ND to 23.1% in Barnstable Town, MA. Metropolitan areas also differ substantially in the time variation of unemployment over time: the area with the smallest fluctuations is Anchorage, AK, in which the unemployment rate ranged between 5.4% and 7.4%, whereas Elkhart-Goshen, IN experienced swings between 2.5% and 18.1%. If anything, the variation in robot adoption across MSAs is even larger, since the metropolitan-level standard deviation of robot per employee is twice as large as its average value.[3]

Importantly, our specification of regression (1) extends the approach of Hazell et al. (2022), that leverages cross-sectional information for identifying the slope of the Phillips curve, to incorporate the role of automation. In a setting which abstracts from robot adoption (i.e., imposing $\gamma = \zeta = 0$), Hazell et al. (2022) show that the estimate of the coefficient β in regression (1) can be mapped into the aggregate slope of the Phillips curve implied by a multi-region model. This result hinges on the following conditions. First, the cross-sectional setting allows us to saturate the regression with year fixed effects, which absorb the endogenous response of monetary policy to common demand shocks, and capture the time-variation in common inflation expectations and supply shock realizations across metropolitan areas. Second, MSA fixed effects control for fixed unobserved heterogeneity across areas, such as time-invariant differences in inflation expectations.

[2] As shown in Basso and Rachedi (2021), considering the interaction term of the unemployment rate with the demeaned robot-per-employee ratio, $m_{i,t-1} - \bar{m}$, does not alter the estimation of how robot adoption affects the relationship between inflation and unemployment. Rather, this normalization allows us to directly interpret the parameter β as the sensitivity of non-tradable goods inflation to the unemployment rate for a MSA with the average degree of robot adoption, that is, when $m_{i,t} = \bar{m}$.

[3] There is also substantial heterogeneity in robot penetration between 2008 and 2018 across areas, going from barely any change in Lewiston, ID-WA up to a 30-fold increase in Hinesville, GA.

Notwithstanding, this setting would not suffice to identify the slope of the Phillips curve because the presence of local idiosyncratic supply shocks, which may be correlated with local unemployment rates, could bias the estimate of β, as discussed by McLeay and Tenreyro (2020). To purge the variation in local unemployment rate from idiosyncratic supply shocks, we follow Hazell et al. (2022) and instrument the unemployment rate with local tradable demand spillovers. Specifically, the local tradable demand spillovers in area i at year t equals

$$\text{Tradable Demand}_{i,t} = \sum_{x} \bar{s}_{x,i} \times \Delta \log s_{-i,x,t}, \tag{2}$$

where $s_{x,i}$ denotes the average value-added share of industry x in the metropolitan area i, and $\Delta \log s_{-i,x,t}$ is the log change in the national real value added of sector x excluding the contribution of the MSA i at year t. In other words, local tradable demand spillovers are defined as a shift-share variable in the spirit of Bartik (1991). As long as supply disturbances that may drive the time variation in national industry value added are not correlated with the heterogeneous relevance of industry value added across areas, the tradable demand spillovers provide a valid instrument.[4] As in Mian and Sufi (2014), the tradable industries are agriculture, mining, and manufacturing.

Since automation could be driven by local demand factors related to the dynamics of wages, prices, and the conditions of the labor market in each metropolitan area, we sharpen our identification of the effect of robot adoption on the relationship between inflation and unemployment following Acemoglu and Restrepo (2020a). In particular, we instrument the robot-to-employee ratio at the MSA-year pair with an alternative measure which replaces the robot installations for each industry at the U.S. national level with the average robot installation per industry in the largest five European economies. Under the identifying restriction that robot demand shocks are weakly correlated across advanced countries, our instrumenting strategy isolates the supply-side component which caused the surge in efficiency of robots, and thus boosted their widespread usage.

We also study the effect of robots on the sensitivity of wage inflation to unemployment by considering a setting identical to regression (1), with the only difference that the dependent variable is $\pi_{W,i,t}$, defined as the log-difference in the average compensation per job of MSA i at year t. This case allows us to

[4] Although the tradable demand spillovers are defined as a shift-share variable as for the case of automation, we use industry value-added shares for the former and industry employment shares for the latter. In this way, we make sure that the two variables do not strongly co-move. In our sample, the correlation between the tradable demand instrument and the robot adoption variable is 0.2.

study whether automation alter the relationship between wage changes and unemployment, and to what extent robot adoption implies a differential sensitivity of unemployment for wage and price inflation.

2.3 Results

Panel A of Table 1 reports the results on how automation alters the sensitivity of non-tradable goods inflation to unemployment. Columns (1) and (2) focus on a case of regression (1) which abstracts from the interaction between robot adoption and the unemployment rate, with the only difference that Column (1) uses OLS methods whereas Column (2) instruments unemployment with tradable demand spillovers. The OLS estimate of the sensitivity of price inflation to unemployment equals -0.1884, is highly statistically significant, and its magnitude is in line with previous estimates of Hazell et al. (2022), while being substantially lower than those of McLeay and Tenreyro (2020). However, the results of Column (2) provide a much steeper relationship between unemployment and inflation, with an estimate of β that equals -0.7031, slightly above the IV estimate of McLeay and Tenreyro (2020) that leverages variation in government spending across metropolitan areas. Our results are consistent also with the evidence of Hazell et al. (2022) and Fitzgerald et al. (2023), that point out how using variation across regional areas leads to a much steeper relationship between inflation and unemployment than when focusing on aggregate data at the national level.

Columns (3) and (4) report the results of the baseline regression that includes the interaction of robot adoption and unemployment, estimated with OLS and IV methods, respectively. In either case, the role of automation is statistically significant at the 5% confidence level, and the magnitude of the coefficient rises substantially when instrumenting both unemployment with tradable spillovers and robot adoption with that implied by the automation patterns of European countries. The estimated coefficient displays a negative sign, implying that price inflation is less reactive to changes in the local labor market in metropolitan areas with relatively more robots. In other words, automation decouples inflation from unemployment. Importantly, the estimate of the role of automation is also highly economically significant: a one standard deviation in robot adoption reduces the sensitivity of inflation to unemployment by 17% with respect to the sensitivity of the metropolitan area featuring the average value of robots per employee.

Similarly to the different cases presented by Panel A of Table 1, Panel B reports the results on how automation alters the relationship between unemployment and wage inflation. Also in this case the coefficients associated to the inter-

Table 1: Robot Adoption and Inflation across MSAs

	No Interaction Term		Baseline	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
	Panel A — Dependent Variable: $\pi_{N,i,t}$			
$u_{i,t-1}$	-0.1884***	-0.7031***	-0.1884***	-0.5069***
	(0.0226)	(0.1364)	(0.0221)	(0.1381)
$u_{i,t-1} \times (m_{i,t-1} - \bar{m})$			0.0010**	0.0066**
			(0.0004)	(0.0030)
Year Fixed Effects	✓	✓	✓	✓
MSA Fixed Effects	✓	✓	✓	✓
N. Observations	3,205	3,205	3,205	3,205
	Panel B — Dependent Variable: $\pi_{W,i,t}$			
$u_{i,t-1}$	-0.3848***	-1.0341***	-0.3855***	-0.9580***
	(0.0330)	(0.1503)	(0.0330)	(0.2450)
$u_{i,t-1} \times (m_{i,t-1} - \bar{m})$			0.0016**	0.0049**
			(0.0007)	(0.0024)
Year Fixed Effects	✓	✓	✓	✓
MSA Fixed Effects	✓	✓	✓	✓
N. Observations	3,205	3,205	3,205	3,205

Note: The table reports the estimates of panel regressions across U.S. MSAs on annual data from 2008 to 2018. In Panel A, the dependent variable is the inflation rate of non-tradable goods, $\pi_{N,i,t}$. In Panel B, the dependent variable is wage inflation, $\pi_{W,i,t}$. In all regressions, the key independent variables are the lagged value of the unemployment rate, $u_{i,t-1}$, the interaction between the lagged value of the unemployment rate and the lag value of the demeaned robot-adoption variable, $u_{i,t-1} \times (m_{i,t-1} - \bar{m})$. In the IV regressions, the unemployment rate is instrumented with a shift-share variable that captures tradeable demand spillovers, and the robot-adoption variable is instrumented with the industry-level robot penetration in a pool of European countries. All regressions also include the lagged value of the robot-adoption variable, $m_{i,t-1}$, the relative price of non-tradable goods, $p_{N,i,t-1}$, as well as year and MSA fixed effects. Columns (1) and (2) report the results of a regression which abstracts from the interaction between the lagged value of the unemployment rate and the lag value of the demeaned robot-adoption variable, while Columns (3) and (4) report the results of the baseline regression which explicitly incorporates the role of the interaction term. Columns (1) and (3) are estimated using OLS methods, and Columns (2) and (4) are estimated using instrumental variables. Double-clustered standard errors are reported in brackets. *** and ** indicate statistical significance at the 1% and 5%, respectively.

action term between unemployment and automation are statistically significant at the 5% confidence level. Interestingly, while the effect of automation on the implied wage Phillips curve at the MSA level is economically relevant, its magnitude falls short of the magnitude of the effects of robot adoption on the price Phillips curve: a one standard deviation in robot adoption reduces the sensitivity of wage inflation to unemployment by 9% with respect to the sensitivity of the metropolitan area featuring the average value of robots per employee. The smaller effect on the wage Phillips curve relative to the price Phillips curve suggests that robot adoption diminishes the influence of wage inflation onto price inflation.

Overall, this analysis has established three main results: automation reduces (i) the sensitivity of price inflation to unemployment, (ii) the sensitivity of wage inflation to unemployment, and (iii) the pass-through from wages to prices.

2.4 Robustness Check

Our results on the relationship between robot adoption and inflation dynamics are validated in an extensive set of robustness checks. We use this analysis to evaluate the extent to which the effect of automation in decoupling inflation and unemployment holds above and beyond alternative explanations. In particular, we consider three groups of potential confounding factors: differences across metropolitan areas in demographic characteristics, occupational structure, and exposure to international trade. We report these exercises in Appendix A.

First, we show that robot adoption dampens the sensitivity of inflation to unemployment even when including the interaction of the unemployment rate with differences in the age structure of the population across MSA, proxied with either the share of individuals below 30 years old, or the share of individuals above 60 years old. This indicates that the effect of automation on price changes is not related to its relationship with an aging labor force (Basso and Jimeno, 2021; Acemoglu and Restrepo, 2022), and the way in which population aging affects the long-run dynamics of inflation (Aksoy et al., 2019). Our evidence holds even when interacting unemployment with measures capturing differences across MSAs in total labor market participation, and in that of women, black people, and asians, as well as in differences in educational attainments. The role of robot adoption keeps being statistically significant even when including differences in the marginal propensity to consume across areas (Herreño and Pedemonte, 2022).

Second, our results hold above and beyond the interaction of unemployment with differences across MSAs in occupations. In particular, we consider variations in the presence of abstract, routine, manual, as well as offshorable occupations.

These characteristics are relevant as Siena and Zago (2022) document that the flattening of the price Phillips curve is related to the phenomenon of job polarization away from routine occupations, which is also directly related to the offshoring of routine activities toward low labor-cost countries (Autor et al., 2013).

Third, the dampening of the inflation sensitivity to unemployment due to automation is also robust to the introduction of controls for the role of import competition, measured in terms of MSA exposure to Chinese and Mexican imports. Thus, our findings holds above and beyond the way in which variations in import competition alter wage and price inflation dynamics (Forbes, 2019; Heise et al., 2022, 2023).

3 Model

The model extends a standard New Keynesian economy to incorporate robot adoption, in the spirit of Acemoglu and Restrepo (2020a), and search frictions in the labor market.[5] The production side has three layers: (*i*) a varying measure of producers that can post vacancies in the labor market and opt to operate using either labor or machines, (*ii*) a continuum of monopolistically competitive wholesalers, that purchase the goods of producers, convert them into different varieties, and face price setting frictions, and (*iii*) a representative retailer, that purchases the different varieties and assemble them into the final good. Final goods are sold to the household and machine manufacturers, that transform them into machines using a technology subject to robot-specific technological change. The household consists of a continuum of workers, who directly look for a job. Income is pooled at the household level, who collectively decides consumption and asset holdings. The monetary authority sets the nominal interest rate according to a Taylor rule.[6]

3.1 Labor Market

The labor market consists of a set of sub-markets with unit measure, indexed by $\omega \in [0, 1]$. At each point in time, there is a time-varying measure $\Xi_{L,t}$ of producers posting vacancies at a given wage, which we refer to as labor firms. We denote with $v_{\omega,t}$ the number of vacancies in each sub-market, such that $\int_0^1 v_{\omega,t}\,\mathrm{d}\omega = \Xi_{L,t}$, and $W_{\omega,t}$ is the associated nominal wage posted.

On the other side, a time-varying measure N_t of individuals decide in which sub-market to search for a job. We denote by $s_{\omega,t}$ the measure of individuals

[5] The combination of these two features allows us to study how automation influences inflation dynamics by altering workers' bargaining power.

[6] Appendix B provides a graphical description of the structure of the model.

searching in each sub-market, such that $\int_0^1 s_{\omega,t}\,\mathrm{d}\omega = N_t$. If individuals match with a producer, they earn the posted nominal wage, and otherwise they receive no income.[7] Given the number of vacancies and searching workers in each sub-market, the flow of matches, $x_{\omega,t}(v_{\omega,t}, s_{\omega,t})$, is pinned down by the matching function

$$x_{\omega,t}(v_{\omega,t}, s_{\omega,t}) = \xi v_{\omega,t}^{\eta} s_{\omega,t}^{1-\eta}, \tag{3}$$

where η is the elasticity of the matching function with respect to vacancies, and ξ denotes the matching efficiency. Matches last for one period.

Given the matching function (D.1) and the tightness in sub-market ω, $\theta_{\omega,t} = v_{\omega,t}/s_{\omega,t}$, which describes the ratio between number of vacancies and number of searching workers, the probability that a worker finds a job equals

$$p_{\omega,t}\left(\theta_{\omega,t}\right) = \frac{x_{\omega,t}(v_{\omega,t}, s_{\omega,t})}{s_{\omega,t}} = \xi\theta_{\omega,t}^{\eta} \tag{4}$$

and the probability that a firm fills a vacancy is

$$q_{\omega,t}\left(\theta_{\omega,t}\right) = \frac{x_{\omega,t}(v_{\omega,t}, s_{\omega,t})}{v_{\omega,t}} = \xi\theta_{\omega,t}^{\eta-1}. \tag{5}$$

The payoff of workers searching in sub-market ω equals the product between the nominal wage rate in case of a match and the probability of finding a job:

$$J_{\omega,t} = p_{\omega,t}(\theta_{\omega,t})\, W_{\omega,t}. \tag{6}$$

Workers decide in which sub-market to search for a job trading off the wage rate and the probability to find a job. In a symmetric equilibrium, workers' payoff should be equalized across all active sub-markets, such that $J_{\omega,t} = J_t$ for all ω. Consequently, sub-markets offering higher wage rates feature lower probabilities to find a job (and higher vacancy filling probabilities from the firms' perspective).

The equilibrium in the labor market implies that the sum of individuals searching in all sub-markets equals the measure of individuals actively looking for a job,

$$N_t = \int_0^1 s_{\omega,t}\,\mathrm{d}\omega. \tag{7}$$

At the end of the period, the unemployment rate depends on the measure of individuals actively looking for a job and those that have matched with a producer,

$$u_t = \frac{N_t - \int_0^1 p_{\omega,t}(\theta_{\omega,t}) s_{\omega,t}\,\mathrm{d}\omega}{N_t}. \tag{8}$$

3.2 Producers

At each point of time, there is a measure Ξ_t of producers that decide to pay a per-period fixed nominal operating cost κ to enter the market. We index each

[7] We abstract from unemployment benefits as we assume perfect consumption insurance within households.

producer with $j \in [0, \Xi_t]$. Upon entry, producers draw an idiosyncratic efficiency in operating with a labor technology, γ_j, from a distribution $f(\gamma)$ with support $[\gamma_M, \gamma_H]$, where γ_M and γ_H are the minimum and maximum labor efficiency levels.

After drawing the labor efficiency, producers decide to operate employing either machines (i.e., robot firms) or workers (i.e., labor firms). In case a producer decides to operate using machines, it purchases a robot from machine manufacturers at price $P_{M,t}$. Robot firms produce with certainty using a linear technology with efficiency γ_M – at the lower bound of producers' labor efficiency[8] – and sell their output to wholesalers at price $P_{P,t}$. The nominal value of robot firms equals the value of sales net of the cost of purchasing a machine and the entry cost,

$$V_{M,j,t} = P_{P,t}\gamma_M - P_{M,t} - \kappa. \tag{9}$$

Since all robot firms operate at the same efficiency, they all share the same value, such that $V_{M,j,t} = V_{M,t}$, for all j.

In case a producer decides to operate using labor, it opens a vacancy in a given sub-market at the nominal wage rate $W_{\omega,t}$. Upon filling the vacancy, the labor firm produces using a linear technology at the labor efficiency rate γ_j, and sells its output to wholesalers at price $P_{P,t}$. Consequently, the nominal value of a labor firm equals the value of sales net of the wage rate, multiplied by the probability of filling the vacancy, minus the entry cost,

$$V_{L,t}(\gamma_j) = q_{\omega,t}(\theta_{\omega,t})\left[P_{P,t}\gamma_j - W_{\omega,t}\right] - \kappa. \tag{10}$$

Labor firms decide the nominal wage rate associated to their vacancies to maximize their value given the labor market tightness and subject to preserving a positive payoff for workers in each sub-market. Optimality – incorporating how the vacancy filling probability, $q_{\omega,t}$, depends on $W_{\omega,t}$ – implies the following nominal wage[9]

$$W_{\omega,t} = P_{P,t}\gamma_j(1-\eta). \tag{11}$$

In other words, the variation in wages across labor firms is uniquely pinned by the dispersion in the labor efficiency values. This result implies that in equilibrium firms with different efficiency levels, γ_j, sort themselves into different sub-markets, ω. Since the labor efficiency is assigned randomly, hereafter we use firms' labor efficiency levels to denote the sub-markets. As such, we refer to wage

[8] In the model, given the entire set of parameters, automation is pinned down by the level of robot-specific technological change. Assuming that robot efficiency is at the lower end of the labor efficiency levels or higher up does not alter the model implications on how automation affects inflation dynamics.

[9] See the Appendix B.1 for the derivation of the nominal wage.

$W_{\gamma_j,t}$ as the rate offered by firms posting a vacancy in the sub-market populated by labor firms with efficiency level γ_j.

How do producers sort into labor firms and robot firms? A producer j opts to open a vacancy and operate the labor technology if and only if the value of being a labor firms is greater than the value of being a robot firm, that is, $V_{L,t}(\gamma_j) > V_{M,t}$. Since the value of being a labor firm increases with the labor efficiency level γ_j,[10] there exists a cut-off point for the labor efficiency level, $\gamma_t^{\star}$, such that

$$V_{L,t}(\gamma_t^{\star}) = V_{M,t}, \tag{12}$$

and firms are indifferent between operating the labor technology or the machine technology. The cut-off point crucially defines the automation choices: producers with a labor efficiency level above $\gamma_t^{\star}$ become labor firms, whereas the rest become robot firms. Consequently, machines displace low-wage jobs associated with low-efficient firms, in line with the evidence of Acemoglu and Restrepo (2018, 2020b).

Given the cut-off point, we can characterize the measure of labor firms and robot firms in the economy. The measure of labor firms integrates across all the producers with an efficiency above $\gamma_t^{\star}$,

$$\Xi_{L,t} = \Xi_t \int_{\gamma_t^{\star}}^{\gamma_H} f(\gamma)\, \mathrm{d}\gamma, \tag{13}$$

and the measure of robot firms captures all producers with sufficiently low labor efficiency:

$$\Xi_{M,t} = \Xi_t \int_{\gamma_M}^{\gamma_t^{\star}} f(\gamma)\, \mathrm{d}\gamma. \tag{14}$$

In equilibrium, the sum of the measures of labor firms and robot firms equals the total amount of producers that have entered the market, that is, $\Xi_{L,t} + \Xi_{M,t} = \Xi_t$.

Given the measure of labor firms and robot firms, we can define the total amount of goods produced by producers, Z_t, as

$$Z_t = \Xi_t \int_{\gamma_t^{\star}}^{\gamma_H} q_{\gamma_j,t}(\theta_{\gamma_j,t})\gamma_j \,\mathrm{d}j + \Xi_{M,t}\gamma_M. \tag{15}$$

Next, we characterize the measure of producers entering the market. In equilibrium, the expected value of any firm entering the market, $V_{E,t}$, must equal zero:

$$V_{E,t} = \int_{\gamma_M}^{\gamma_t^{*}} V_{M,t} f(\gamma)\mathrm{d}\gamma + \int_{\gamma_t^{*}}^{\gamma_H} V_{L,t}(\gamma_j) f(\gamma)\mathrm{d}\gamma = 0. \tag{16}$$

Finally, as a single statistics that allows us to track the overall variation in

[10] See Appendix B.1 for a proof of this property.

wages, we define the average wage as

$$W_t = \frac{(1-\eta)P_{P,t}\Xi_t}{\Xi_{L,t}} \int_{\gamma_t^*}^{\gamma_H} \gamma_j f(\gamma) \mathrm{d}\gamma. \tag{17}$$

3.3 Wholesalers

There is a unit measure of monopolistically competitive wholesalers, indexed by $i \in [0,1]$. Each wholesaler purchases goods $Z_{i,t}$ from the producers at price $P_{P,t}$, and transforms them into a different variety $Y_{i,t}$ with the linear technology:

$$Y_{i,t} = Z_{i,t}. \tag{18}$$

The varieties are sold to retailers at price $P_{i,t}$. Then, wholesalers' profits equal to $P_{i,t}Y_{i,t} - P_{P,t}Z_{i,t}$.

Wholesalers face price-setting friction in the form of a Rotemberg adjustment cost, denoted by the parameter ϕ. Wholesalers optimally set their price $P_{i,t}$ by maximizing expected profits net of the Rotemberg costs

$$\max_{P_{i,t}} \mathbb{E}_t \left\{ \sum_{k=t}^{\infty} Q_{k,t} \left(P_{i,k}Y_{i,k} - P_{P,k}Z_{i,k} - \frac{\phi}{2} \left[\frac{P_{i,k}}{P_{i,k-1}} - 1 \right]^2 Y_{i,k} \right) \right\}, \tag{19}$$

where $Q_{k,t}$ is households' stochastic discount factor. In a symmetric equilibrium, all wholesalers set the same price, such that $P_{i,t} = P_t$ for all i. We denote by $\pi_t = \frac{P_t}{P_{t-1}}$ the inflation rate.

The market clearing condition implies that the total amount of goods produced by the wholesalers — net of the Rotemberg adjustment cost — equals those produced by both labor firms and machine firms,

$$\int_0^1 \left[1 - \frac{\phi}{2} \left(\frac{P_{i,t}}{P_{i,t-1}} - 1 \right)^2 \right] Y_{i,t} \, \mathrm{d}i = \int_0^1 Z_{i,t} \, \mathrm{d}i = Z_t. \tag{20}$$

3.4 Retailers

There is a perfectly competitive representative retailer that purchases all the varieties from the wholesalers, $Y_{i,t}$, and assembles them into the final good of the economy, Y_t, with a CES technology:

$$Y_t = \left[\int_0^1 Y_{i,t}^{\frac{\epsilon-1}{\epsilon}} \, \mathrm{d}i \right]^{\frac{\epsilon}{\epsilon-1}}, \tag{21}$$

where ϵ is the elasticity of substitution across varieties. The retailer sells the final goods at price P_t to households and machine manufacturers. Retailers' optimal demand of each variety is

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\epsilon} Y_t, \tag{22}$$

where the price of final goods is given by

$$P_t = \left[\int_0^1 P_{i,t}^{1-\epsilon} \, \mathrm{d}i \right]^{\frac{1}{1-\epsilon}}. \tag{23}$$

Final goods are sold to household, in form of consumption goods C_t, and to machine manufacturers, in form of investment goods I_t, such that

$$Y_t = C_t + I_t. \tag{24}$$

3.5 Machine Manufacturers

There is a perfectly competitive representative machine manufacturer that purchases final goods from the retailer I_t at price P_t, and transform them into machines M_t with the linear technology

$$M_t = \zeta I_t, \tag{25}$$

where ζ is the level of robot-specific technological change. The manufacturer sells the machines to robot firms at price $P_{M,t}$. This price inversely relates to the level of technological change:

$$P_{M,t} = \frac{1}{\zeta} P_t. \tag{26}$$

A higher value of robot-specific technological change implies that the production of machines is becoming relatively more efficient. Consequently, the price of machines goes down.

In equilibrium, the total amount of machines sold by the manufacturer equals the machines demanded by the robot firms (i.e., the measure of robot firms):

$$M_t = \Xi_{M,t}. \tag{27}$$

3.6 Households

The household consists of a unit measure of individuals with perfect consumption insurance. Individuals are denoted by $x \in [0,1]$. Given total nominal labor earnings X_t, which we describe below, the household decides the optimal levels of consumption, C_t, to purchase from retailers at price P_t, and savings in one-period nominal bonds, B_t. Specifically, the household maximizes its lifetime utility

$$\max_{C_t, B_{t+1}} \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \Omega_t \frac{C_t^{1-\sigma}}{1-\sigma} \tag{28}$$

$$\text{s.t. } P_t C_t + B_t = B_{t-1} R_{t-1} + X_t \tag{29}$$

where R_t denotes the nominal interest rate, and Ω_t is an exogenous preference shifter that follows the autoregressive process

$$\log \Omega_t = \rho_\Omega \log \Omega_{t-1} + \varepsilon_{\Omega,t}, \tag{30}$$

in which ρ_Ω is the auto-regressive parameter, and $\varepsilon_{\Omega,t}$ is a preference shock.[11]

To account for endogenous labor market participation, we allow individuals to decide whether to actively look for a job. To do so, we assume that each individual draws a searching cost, λ_x, from a uniform distribution, $U(\lambda)$, with support $[0, \lambda_H]$. Consequently, individuals decide to search for jobs only when their expected discounted value of searching exceeds the searching cost, that is

$$J_t / U_{C,t} \geq \lambda, \tag{31}$$

where $U_{C,t}$ is the marginal utility of consumption. After the individuals have decided whether or not to search and the matches are realized, all the nominal labor earnings X_t are pooled together within the household, such that

$$X_t = \Xi_t \int_{\gamma_t^\star}^{\gamma_H} q_{\gamma_j,t}\left(\theta_{\gamma_j,t}\right) W_{\gamma_j,t} f(\gamma)\, \mathrm{d}\gamma. \tag{32}$$

In other words, taking the nominal wage rate of all the sub-markets/efficiency levels which are not automated and multiplying them with the associated probability to find a job yields the aggregate labor earnings of the household.

3.7 Monetary Authority

The monetary authority sets the nominal interest rate R_t following a Taylor rule that reacts to the inflation rate, π_t, and the unemployment gap, u_t/u_t^F, where u_t^F is the unemployment rate in the flexible-price economy, such that

$$R_t/\bar{R} = \left[R_{t-1}/\bar{R}\right]^{\psi_R} \left[(1+\pi_t)^{\psi_\pi} \left(u_t/u_t^F\right)^{\psi_u}\right]^{1-\psi_R}, \tag{33}$$

where $\bar{R}$ is the steady-state nominal interest rate,[12] ψ_R captures the degree of interest-rate smoothing, and ψ_π and ψ_u denote the responsiveness of interest rates to the inflation rate and the unemployment gap, respectively.

4 Quantitative Analysis

This section evaluates how and to what extent automation alters inflation dynamics in the model. To perform this analysis, we start by describing the calibration of the model in Section 4.1. Section 4.2 characterizes the effect of automation on the slope of the price Phillips curve, and Section 4.3 performs a similar analysis looking at the wage-to-price pass-through. In Section 4.4, we quantify to what extent automation can account for the flattening of the Phillips curve estimated in our empirical evidence. Section 4.5 isolates — and measures the relevance of — the different mechanisms of the model through which robot adoption affects

[11] Our analysis focuses on the dynamics of inflation amidst the realization of preference shocks. However, we also evaluate the robustness of the results to the case of monetary policy and productivity shocks.

[12] Throughout the paper, we denote by $\bar{A}$ the steady-state value of variable A_t.

inflation dynamics. Finally, Section 4.6 shows that our model can also account for the resurgence of a steep Phillips curve insofar ramping-up automation is costly, and the economy is hit by large expansionary shocks.

4.1 Calibration

We calibrate the model to the U.S. economy by considering that one period corresponds to a quarter. We consider a zero net inflation rate in the steady state. We start by setting households' risk aversion parameter to the standard value of $\sigma = 2$, while the time discount factor is $\beta = 0.995$ to imply a 2% annual real interest rate at the steady state.

Regarding producers' efficiency in using the labor technology, we assume that the labor efficiency γ_j is drawn from a Truncated Pareto Distribution with location parameters, γ_M and γ_H, and shape parameter, α, so that $f(\gamma) = \frac{\alpha {\gamma_M}^{\alpha} \gamma_j^{-\alpha-1}}{1-{\gamma_M}^{\alpha} {\gamma_H}^{-\alpha}}$. We normalize the lower bound of the labor efficiency – and thus robots' productivity – to $\gamma_M = 1$. We set the highest value in the support to imply that the most productive firms in the economies have a 10% higher efficiency in using the labor technology that the least productive ones. This implies that $\gamma_H = 1.1$. Then, to ensure that both the vacancy filling probability and the job finding probability are within zero and one, we set the scale parameter, $\alpha = 5$, and the matching efficiency, $\xi = 0.92$. The elasticity of labor matches with respect to vacancies equals $\eta = 0.5$ following the evidence of Petrongolo and Pissarides (2001). To close the labor market block, we set the fixed cost of entry, $\kappa = 0.42$, and the searching cost, $\lambda = 1.8$, such that the unemployment rate is 5.7%, and the participation rate is 63%, in line with the average rates observed in the 2010's in the U.S.

For any given parametrization of the labor efficiency distribution, the level of the robot-specific technological change pins down the amount of automation. We discipline it such that our model is consistent with the 0.2% robot to employee ratio documented for the U.S. in the early 2000s by Acemoglu and Restrepo (2020a), after taking care the conversion of the full-time employees of our model to the mix of full-time and part-time in the data. To match this target, we set $\zeta = 2$.

On the production side, the elasticity of substitution across varieties is $\epsilon = 9$, so that the markup is 12.5%, in the ball park of the values used in New Keynesian models (see Christiano et al., 2005). We set the Rotemberg adjustment cost parameter to $\phi = 94.6$ to target a 12 month duration of prices on average.

Regarding the monetary authority, we discipline the parametrization of the Taylor rule following the estimates of Clarida et al. (2000). Accordingly, the inertia parameter equals $\psi_R = 0.8$, the degree of response to the inflation rate is $\psi_\pi = 1.5$, and the degree of response to the unemployment gap is $\psi_u = -0.2$. Finally, we set the auto-regressive coefficient of the demand shock to $\rho_\Omega = 0.9$, in line with the evidence of Justiniano and Primiceri (2008).

Table 2: Calibration Values

Parameter	Description	Value	Source/Target
σ	Risk Aversion	2	Standard
β	Time Discount Factor	0.995	2% Steady-State Annual Real Rate
γ_M	Robot Efficiency	1	Normalization
γ_H	Upper Bound Labor Efficiency	1.1	10% Efficiency Wedge
α	Scale Labor Efficiency Distribution	5	$0 \leq p_{\gamma_j,t}\left(\theta_{\gamma_j,t}\right) \leq 1$
ξ	Efficiency Matching Function	0.92	$0 \leq q_{\gamma_j,t}\left(\theta_{\gamma_j,t}\right) \leq 1$
κ	Entry Cost	0.42	$\bar{u} = 5.7\%$
λ	Searching Cost	1.8	$\bar{N} = 63\%$
η	Elasticity Labor Matches to Vacancies	0.5	Petrongolo and Pissarides (2001)
ϵ	Elasticity of Substitution Wholesalers' Varieties	9	12.5% Markup
ϕ	Rotemberg Cost	94.6	Average 12 Month Price Duration
ζ	Robot-Specific Technological Change	2	0.2% Steady-State Robot per Employee
ψ_R	Taylor Rule Inertia	0.8	Clarida et al. (2000)
ψ_π	Taylor Rule Responsiveness to Inflation	1.5	Clarida et al. (2000)
ψ_u	Taylor Rule Responsiveness to Unemployment Gap	-0.2	Clarida et al. (2000)
ρ_Ω	Persistence Demand Shock	0.9	Justiniano and Primiceri (2008)

Note: The table reports and briefly explains the calibration values of all the model parameters.

4.2 Characterization of the Slope of the Phillips Curve

How does automation alter inflation dynamics in the model? To address this question, we first characterize the slope of price Phillips curve. To derive it, we log-linearize the model around the steady state, and incorporate the labor market and wholesalers' equilibrium conditions into the pricing equation. In this way, we determine the relationship between price inflation and unemployment. In what follows, we denote by $\hat{A}_t$ the log deviations of variable A_t from its steady state $\bar{A}$.

Let $\Theta \equiv \{\eta, \gamma_M, \gamma_H, \alpha, \epsilon\}$ represent a set of key structural parameters, that is, the elasticity of matches with respect to vacancies, the efficiency in employing machines, the upper bound of the efficiency in employing workers, the scale parameter of the labor efficiency distribution, and the elasticity of substitution across wholesalers' varieties, and $\bar{\gamma}^{\star}$ the cut-off point that determines the share of production that is automated at the steady state. The Phillips Curve is then given by[13]

$$\hat{\pi}_t = -\frac{\epsilon-1}{\phi}\Psi(\bar{\gamma}^{\star};\Theta)(\hat{u}_t - \hat{u}_t^F) + \beta\frac{\epsilon-1}{\phi}\mathbb{E}_t\hat{\pi}_{t+1}, \tag{34}$$

where the slope of the Phillips curve depends on $\Psi(\bar{\gamma}^{\star};\Theta)$, which is a function of structural parameters and steady-state values, such that

$$\Psi(\bar{\gamma}^{\star};\Theta) = \frac{\bar{u}}{1-\bar{u}}\,\frac{1-\eta}{\eta + [\eta(\epsilon-1)/(\gamma_M\epsilon\varpi_1)]\left[\varpi_2 - \varpi_3(1-\eta)(1+\varpi_2)\right]}, \tag{35}$$

and the auxiliary variables ϖ_1, ϖ_2, and ϖ_3 equal:

$$\varpi_1 = \xi\left[\eta\frac{\epsilon-1}{\epsilon}\right]^{\eta}\bar{\gamma}^{\star}\Big/\left\{(1-\bar{u})\bar{\gamma}^{\star}\left[\frac{1-(\gamma_H/\bar{\gamma}^{\star})^{\frac{1}{\eta}-\alpha}}{1-(\gamma_H/\bar{\gamma}^{\star})^{\frac{(1-\eta)}{\eta}-\alpha}}\right]\left(1+\frac{\eta}{\alpha\eta-1}\right)\right\}^{1-\eta},$$

$$\varpi_2 = \left[1-\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha}\right]\Big/\left\{\frac{\alpha\eta}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha} - \left(\frac{\gamma_M}{\gamma_H}\right)^{\alpha}\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{1/\eta}\right]\right\},$$

$$\varpi_3 = \left(\alpha - \frac{1-\eta}{\eta}\right)\left[1-\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{\frac{(1-\eta)}{\eta}-\alpha}\right]^{-1} - \left(\alpha-\frac{1}{\eta}\right)\left[1-\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{\frac{1}{\eta}-\alpha}\right]^{-1}.$$

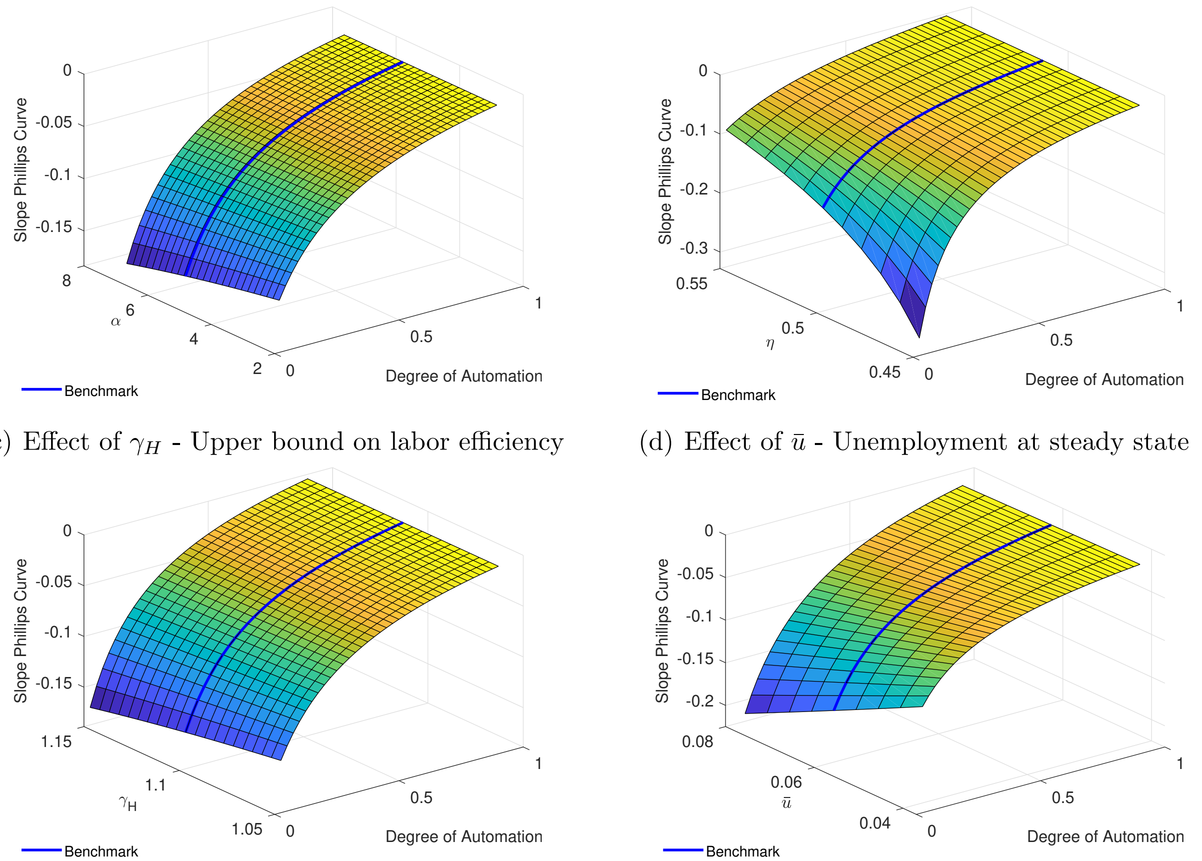
Unlike standard New Keynesian models, in our econonomy the slope of the Phillips curve is not only a function of firms' markups, captured by the elasticity of substitution across wholesalers' varieties ϵ, and the degree of nominal rigidity, captured by the Rotemberg cost ϕ, but also depends on the degree of automation through the automation threshold $\bar{\gamma}^{\star}$. Consequently, changes in robot adoption do alter inflation dynamics in the model.

How can we evaluate how and to what extent automation affects the price Phillips curve? As we have mentioned in the calibration in Section 4.1, the degree of automation in the model crucially depends on the level of robot-specific technological change, ζ, that pins down the relative price of machines in terms of final goods, $P_{M,t}/P_t$. A higher value of ζ implies that manufacturers are relatively more efficient in producing machines, which curtails the relative price of machines and leads to a larger degree of robot adoption by producers (i.e., $\bar{\gamma}^{\star}$ rises). Consequently, the relative measure of robot firms increases. This is consistent with the evidence of Graetz and Michaels (2018), showing that the price of robots felt during the last decades while automation has been increasing. On the grounds of these premises, we evaluate how a surge in robot-specific technological change – pushing the economy towards a new steady state with relatively lower

[13] We report the details of the derivation of the Phillips curve in Appendix B.3.

prices for machines and higher robot adoption – alters the price Phillips curve.

Figure 1: Degree of automation and the slope of the Phillips curve



(a) Effect of α - Shape of labor efficiency distribution (b) Effect of η - Elasticity of matches to vacancies

(c) Effect of γ_H - Upper bound on labor efficiency (d) Effect of $\bar{u}$ - Unemployment at steady state

Note: The figures show how the slope of the Phillips curve of the model varies with the degree of robot automation, that crucially depends on the level of robot-specific technological change ζ.

Since we cannot unequivocally sign the derivative of the slope of the price Phillips curve with respect to changes in robot-specific technological change, we use the closed-form specification of Equation (34) to numerically characterize how inflation dynamics varies with changes in the relative measure of robot firms. To do so, we compute the slope by varying both the level of the robot-specific technological change, ζ, as well as each of the other key structural parameters that influence the inflation sensitivity to unemployment, one at a time. Figure 1 shows the results of this exercise, in which we study how the slope varies with the interaction of automation with the shape of the labor efficiency distribution, α, in Panel (a), the elasticity of labor matches to vacancies, η, in Panel (b), the upper bound on the value of the efficiency of employing the labor technology, γ_H, in Panel (c), and the steady-state unemployment rate, $\bar{u}$, in Panel (d). In each panel, the degree of automation is defined as the relative measure of robot firms implied by different levels of robot-specific technological change.[14]

The results of Figure 1 highlight four main findings. First, automation unambiguously decreases the slope of the price Phillips curve, independently on the values of all the other key parameters of the model. Thus, robot adoption reduces the sensitivity of inflation to the unemployment gap. Second, the flattening effect of automation is pronounced at lower values of the elasticity of labor matches to vacancies, η. Third, robot adoption leads to larger changes in the slope when there is a relatively larger fraction of producers with low labor efficiency levels, which is captured by the slope parameter α. In this case, robot-specific technological change triggers a more pronounced adoption of machines, leading to a significant flattening of the Phillips curve. Fourth, automation alters the way in which the steady-state level of unemployment influences the slope of the Phillips curve. At low automation levels, the slope raises with the unemployment level. Instead, when robot adoption is large enough, steady-state unemployment has no effect whatsoever on the slope.

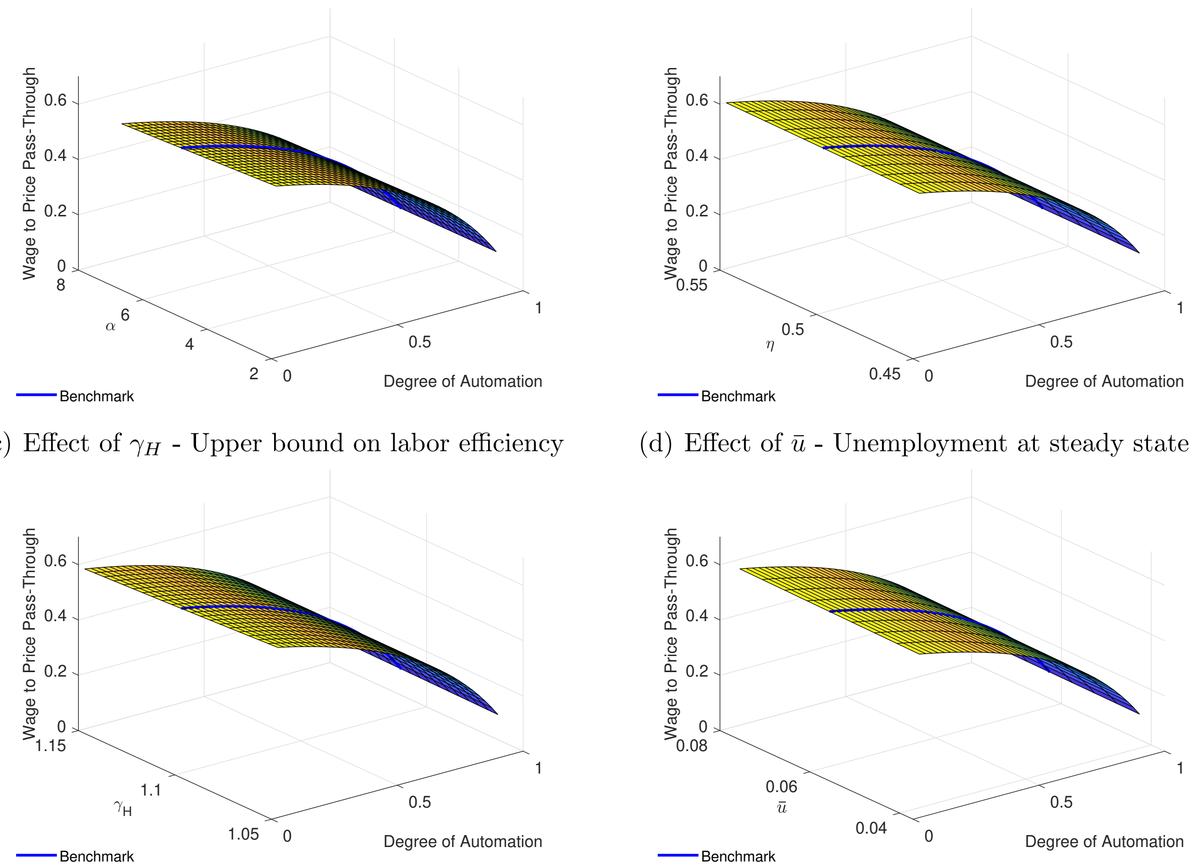
4.3 Characterization of the Wage-to-Price Passthrough

To what extent the flattening effect on automation on the price Phillips curve hinges on the way in which robot adoption alters the pass-through from wages into prices? On the one hand, automation provides an option to producers to replace workers with machines. Consequently, it shrinks workers' bargaining power. On the other hand, a larger measure of robot firms reduces the labor share of the economy, as output can be produced with fewer workers. As a result, price inflation decouples from wage inflation.

This section characterizes the way in which the degree of automation alters the wage-to-price pass-through in a similar spirit to the previous analysis on the slope of the Phillips curve. Specifically, we use the condition that determines the average wage in Equation (17) and characterize the way in which it relates to the changes in producers' price, $P_{P,t}$. Since producers' price defines the marginal cost for wholesalers, this analysis allows us to isolate the relationship between

[14] These exercises are performed with the parameter values implied by our calibration in Section 4.1. In all exercise and unless mentioned otherwise, all parameters — but robot adoption and one additional key parameter in each panel — are set at their calibrated values. The blue continuous line indicates how the slope varies solely with changes in automation, assuming all other parameters are set at their baseline values.

Figure 2: Degree of automation and the wage to price pass-through



(a) Effect of α - Shape of labor efficiency distribution (b) Effect of η - Elasticity of matches to vacancies

(c) Effect of γ_H - Upper bound on labor efficiency (d) Effect of $\bar{u}$ - Unemployment at steady state

Note: The figures replicates the analysis of Figure 1 with the difference that the outcome of interest is not the slope of the price Phillips curve but rather the wage-to-price pass-through.

marginal costs and wages. The model implies the following condition:[15]

$$\widehat{P}_{P,t} = \Upsilon(\bar{\gamma}^{\star};\Theta)\hat{W}_t, \tag{36}$$

where the loading factor $\Upsilon(\bar{\gamma}^{\star};\Theta)$ is a convolution of parameters and steady-state values, such that

$$\Upsilon(\bar{\gamma}^{\star};\Theta) = \frac{1}{1+\left[\eta\gamma_M\bar{P}_P\varpi_{pw}\left(1+\varpi_2\right)/\varpi_1\right]}, \tag{37}$$

and the auxiliary variable ϖ_{pw} equals

$$\varpi_{pw} = \frac{\bar{\gamma}^{\star\,-\alpha}\left(\bar{\gamma}^{\star\,-\alpha}-\gamma_H^{-\alpha}\right)+\alpha(\bar{\gamma}^{\star}\gamma_H)^{-\alpha}(\bar{\gamma}^{\star}-\gamma_H)}{\left(\bar{\gamma}^{\star\,-\alpha}-\gamma_H^{-\alpha}\right)\left(\bar{\gamma}^{\star\,1-\alpha}-\gamma_H^{1-\alpha}\right)}.$$

The loading factor $\Upsilon(\bar{\gamma}^{\star};\Theta)$ provides a measures of the wage to price pass-through. We then verify how $\Upsilon(\bar{\gamma}^{\star};\Theta)$ changes with the degree of automation and the structural parameters, as we have done for the analysis on the slope

[15] See Appendix B.4 for the derivation of the wage-to-price pass-through.

of the Phillips Curve, and report the results in Figure 2. We find that robot adoption leads to a drop of the wage-to-price pass-through, which is particularly pronounced at high levels of automation.

4.4 Quantification of the Flattening due to Automation

This section quantifies the effect of automation on the flattening of the price and wage Phillips curves. To perform this exercise, we compare the slope of the Phillips curve of two economies with two distinct steady states that uniquely differ in the level of robot-specific technological change, and thus on the degree of automation. As for the first economy, we consider the steady state defined by the calibration of Section 4.1, in which the robot-to-employee ratio targets the 0.2% documented by Acemoglu and Restrepo (2020a) for the early 2000s in the U.S. We refer to this case as the *low automation* economy. As for the second economy, we consider a steady state with a relatively higher amount of automation. To discipline robot adoption across the two steady states, we refer to our data on the dispersion of the robot-to-employee ratio across metropolitan areas. In the panel, a one standard deviation increase in robot penetration across MSAs raises the ratio of robots to employees by 200%. Accordingly, we calibrate the level of robot-specific technological change in the second economy such that it features a robot-to-employee ratio of 0.6%. We refer to this case as the *high automation* economy.

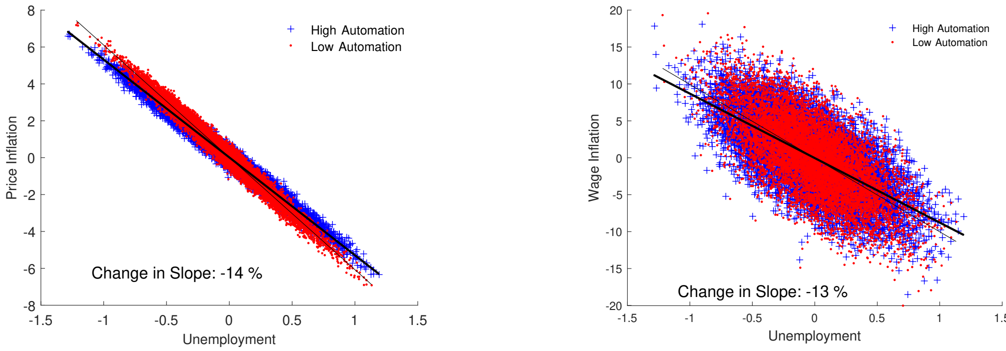
We simulate the two economies by considering 10,000 realizations of the preference shock, and use the implied values of inflation and the unemployment rate to graphically characterize the price and wage Phillips curves in both the *low automation* and *high automation* model.[16] We report the simulated values in Figure 3, together with the implied regression lines of price inflation and unemployment in Panel (a), and wage inflation and unemployment in Panel (b).

We find that automation reduces the slope of the regression line of price inflation across the two steady states by 14%, whereas the flattening of the wage inflation curve amounts to 13%. The drop in the slope of the price Phillips curve accounts for 82% of the one estimated in the data, in which a one standard deviation increase in automation implies a flattening by 17%. However, the model generates an excessive degree of flattening in the wage Phillips curve compared to our empirical evidence (13% vs. 9%), and thus a relatively more muted reduction in the wage-to-price pass-through. From this perspective, the model is consistent with the body of work that emphasizes the key role of the flattening of the wage Phillips

[16] Since we consider demand shocks, the variation in unemployment coincides with that of the unemployment gap. We use the two terms interchangeably throughout the body of the paper.

Figure 3: Simulated Phillips Curves

(a) Price Inflation Phillips Curve (b) Wage Inflation Phillips Curve



Note: The figures reports 10,000 simulations of the low and high automation economies on price inflation and unemployment, in Panel (a), and wage inflation and unemployment, in Panel (b). The inflation rates are annualized and all variables are represented in percentage points.

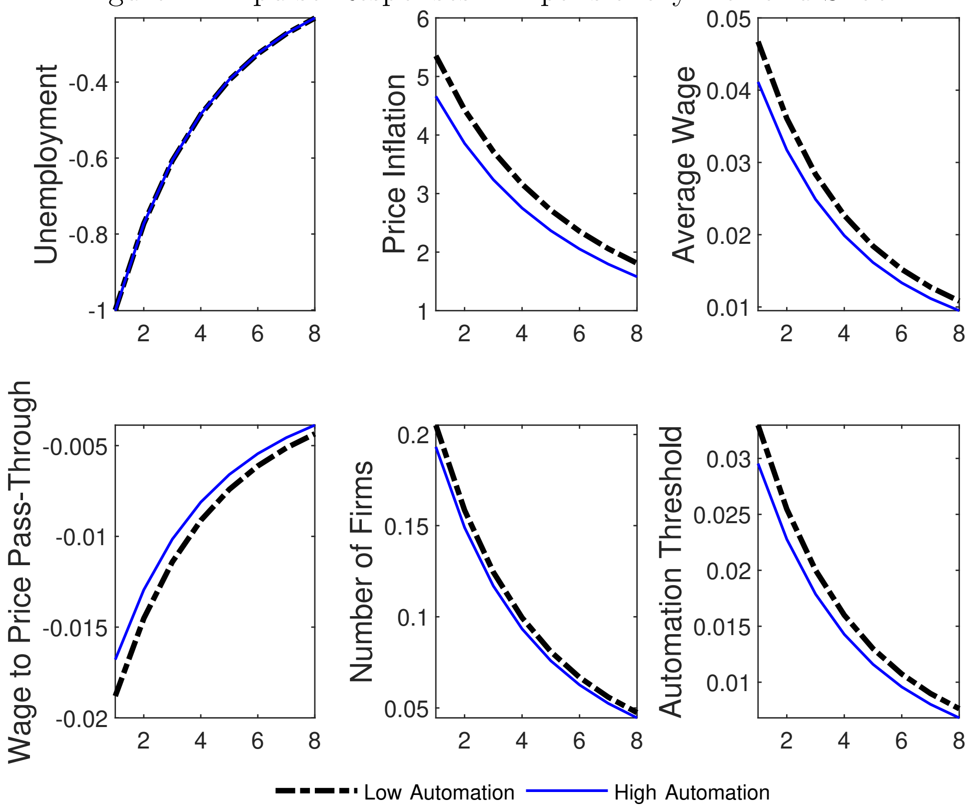
curve in reducing the slope of the price Phillips curve (Stansbury and Summers, 2020; Siena and Zago, 2022; Faccini and Melosi, 2023). However, our economy does not give a quantitatively relevant role to the reduction in the wage-to-price pass-through emphasized by Del Negro et al. (2020) and Heise et al. (2022).

The limited reduction in the wage-to-price pass-through is due to the fact that the effect of automation on the pass-through from wages into prices is pronounced only at later stages of robot adoption, as discussed in Section 4.3. To mitigate this issue, in Appendix we provide an extension of our economy that generates an empirically relevant reduction in the wage-to-price-through due to automation. Specifically, we consider two sectors, one in which wholesalers and retailers produce the consumption goods demanded by the household, and one in which they produce the investment goods demanded by machine manufacturers. The two sectors differ only in the use of physical capital in the technology of wholesalers. As in the data, the investment sector features a much higher capital share. In this model specification, automation raises the relevance of capital return rates into firms' marginal costs, and thus decouples price inflation from wage inflation.

4.5 Inspecting the Mechanism

To inspect the mechanism leading robot adoption to flatten the price Phillips curve, we perform an exercise similar to that of Del Negro et al. (2020) and look at how the responses of price inflation, average wage, the wage-to-price pass-through, the number of firms, and the automation cut-off point to an expansionary demand shock vary across the low automation and the high automation economies.[17] Figure 4 reports the results of this exercise, in which we normalize the response of the unemployment rate to be the same in the two economies.

Figure 4: Impulse Responses - Expansionary Demand Shock



Note: Impulse responses of the unemployment rate (in percentage points), price inflation (in percentage points, annualized), average wage, the wage-to-price pass-through, number of firms and the automation cut-off point (γ^*) to an expansionary demand shock designed to generate similar responses in unemployment in economies with high and low degrees of automation.

When consumer demand exogenously increases, firms' value surges leading to a boost in entry. The number of posted vacancies hikes up, leading to lower unemployment and higher wages. However, a given change in unemployment leads to a relatively more muted response of wages and prices in the high automation economy. The same 1 percentage point drop in unemployment raises inflation on impact by 5.35 percentage points in the low automation economy, and by 4.66 percentage points. This implies a reduction in the inflation responsiveness by 13%.

What drives the decoupling of unemployment and inflation? Automation alters inflation dynamics through three channels. First, higher wages push some firms to replace workers with machines, suppressing labor demand, and exerting

[17]We report the results of a similar exercise looking at the effects of either monetary policy shocks or productivity shocks in the Appendix C.

a downward pressure on the increase in wages. We refer to this channel as the *Cyclical Effect* of automation. Second, since robots are always a choice firms can fall back on, robot adoption reduces workers' bargaining power, dampening the elasticity of wages to unemployment. We refer to this channel as the *Wage Setting Effect* of automation. Third, the high automation economy features a relatively larger share of robot firms. Therefore, part of the adjustment process as a response to the shock occurs independently of the changes in the labor market, decoupling the variation in wages from inflation. We refer to this channel as the *Steady State Effect* of automation.

To isolate each of these channels, we consider four alternative model specifications to our baseline economy. In the first, we fix automation to its steady-state level, such that producers cannot replace workers after a shock. We refer to this case as the *Baseline - Fixed Automation* economy. We then alter the type of search frictions in the labor market, and replace directed search with random search.[18] Specifically, we assume firms and workers are randomly matched and wages are set as a result of Nash bargaining where τ denotes the weight of the workers surplus from the match and thus measures the degree of bargaining power of the worker (see Pissarides, 2000). We consider two cases, one economy in which we set $\tau = \eta = 0.5$, thus labor markets are efficient (Hosios condition) and wages are set to maximize equally weighted measures of the surplus of workers and firms; we refer this case as the *Random Search* - $\tau = 0.5$ economy. The third economy employs random search but sets $\tau = 0.01$, thus almost all the bargaining power resides in the hand of the firms. Finally, for completeness we also consider the model under random search in which automation is fixed its steady-state level, denoting it as the *Random Search - Fixed Automation* economy.[19]

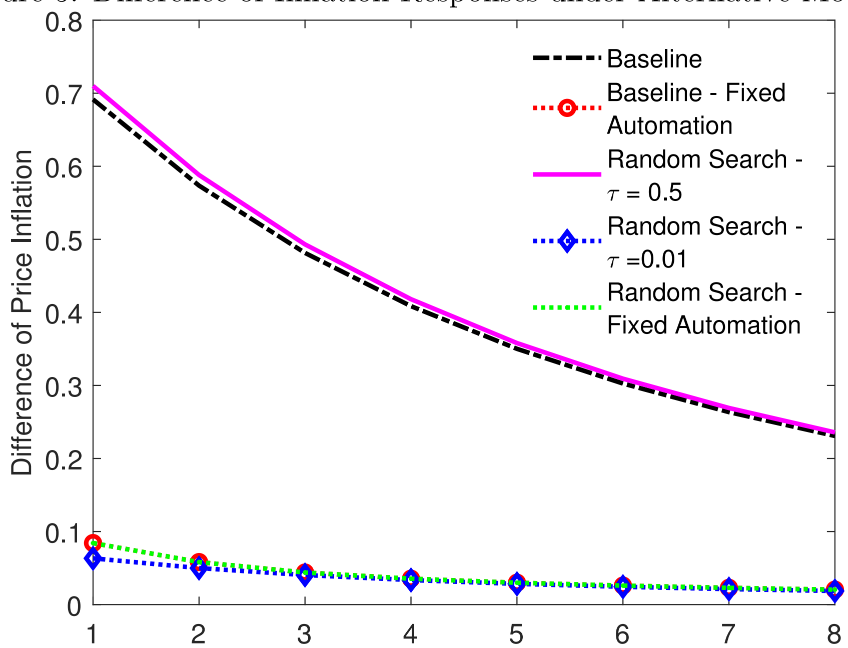
We then report the difference in the inflation response to an expansionary shock for each of these five economies between their low automation and high automation steady states in Figure 5. When automation cannot change upon a shock, neither the *Cyclical Effect* nor the *Wage Setting Effect* are operational, and therefore the only difference between the low automation and high automa-

[18] The model with random search incorporates an additional parameter that describes the degree of bargaining power of workers allowing us to isolate the *Wage Setting effect*. However, despite the firm heterogeneity present in our model, all firms post vacancies on a homogenous labor market, and wage bargaining is done based on the expected level of productivity of the firms posting vacancies. Details of this model extension are available in Appendix D.

[19] The inflation differentials are the same for $\tau = \eta = 0.5$ and $\tau = 0.01$ when automation is fixed. This result further illustrates the importance of the interaction between bargaining power and endogenous automation decisions.

tion economies is the degree of robot adoption at the steady state. The lower labor share in the high automation case implies that wages and prices are less responsive to variation in unemployment. Consequently, the Phillips curve is flatter, independently of the search protocol and the bargaining power. Importantly, the differential response with fixed automation is substantially below the one of the baseline economy, implying that the two missing channels are quantitatively the key drivers of the flattening of the price Phillips curve in our model.

Figure 5: Difference of Inflation Responses under Alternative Models



Note: Figure shows the absolute difference in the price inflation in annualized percentage points in the Low and High Automation economies for each model version, the *Directed Search* is the baseline model, the *Random Search* model assumes random search instead of directed search, the *Directed Search - Fixed* is the baseline model assuming automation is fixed in the short-term and *Random Search - Fixed* is the random search model assuming automation is fixed in the short-term. The Inflation difference is defined as |Impulse Response of *Low Automation* Economy - Impulse Response of *High Automation* Economy|.

To disentangle the role of the *Cyclical Effect* from the *Wage Setting Effect*, we look at the differential response implied by the baseline model with that of the *Random Search* economies. In the first, *Random Search* - $\tau = 0.5$, as in the baseline economy under directed search, labor markets are efficient. In both economies, wages are such that the firm's and worker's gains from the match are equally weighted. As a result, in both economies robot adoption reduces workers' bargaining power, dampening the elasticity of wages to unemployment. In the second, *Random Search* - $\tau = 0.01$ we set the worker's bargaining power to be very low. As such, robot adoption no longer has a significant effect on the elasticity of wages to unemployment since there is no room for the treat of automation to further reduce workers' bargaining power.

On the grounds of this premise, comparing the differential response of the *Random Search* - $\tau = 0.01$ economy with its counterpart with no variation in robot adoption isolates the role of the *Cyclical Effect*, whereas comparing the differential response of the *Random Search* - $\tau = 0.01$ economy with the *Baseline* and *Random Search* - $\tau = 0.5$ economies highlights the significance of the *Wage Setting Effect*. The results of Figure 5 indicate that the bulk of the flattening effect in our model comes from the *Wage Setting Effect* of automation: the threat of robot adoption reduces workers' bargaining power, curtailing the wage responsiveness to unemployment, leading to flat price and wage Phillips curves.

4.6 Automation and the Steepening of the Phillips Curve

The analysis so far has shown that our model can account for the subdued inflation dynamics that has been characterizing advanced economies in the recent decades. However, the Covid recovery has been accompanied by a substantial drop in unemployment and a 30-year record high inflation rates. We show that the fact that in our economy a surge of automation flattens the price Phillips curve is still consistent with the possibility of observing a resurgence in the steepening of the relationship between inflation and unemployment.[20]

While our previous analysis hinged on the assumption that the production of robots is a costless procedure of transforming final goods into machines subject to robot-specific technological change, we relax this condition by considering the empirically relevant case in which ramping-up automation in the short term is costly. Specifically, we extend the production function of machine manufacturers in Equation (25) as follows

$$M_t = \left[\zeta - \Delta\left(I_t/\bar{I}\right)\right] I_t, \tag{38}$$

where $\Delta\left(I_t/\bar{I}\right)$ denotes an asymmetric investment adjustment cost function as in Varian (1975), such that

$$\Delta\left(I_t/\bar{I}\right) = \frac{\delta}{\varrho^2}\left\{\exp\left[\varrho\left(\frac{I_t}{\bar{I}} - 1.05\right)\right] + \varrho\left(\frac{I_t}{\bar{I}} - 1.05\right) - \vartheta\right\}, \tag{39}$$

in which δ controls the magnitude of the cost, ϱ defines the degree of asymmetry (i.e., the adjustment costs become quadratic when $\varrho \to 0$), and ϑ is defined as

[20] For alternative approaches to explain the resurgence of a high inflation, Harding et al. (2022b) proposes a non-linear Phillips curve due to quasi-kinked demand schedules, and Heise et al. (2023) show that supply-chains disruptions reduced the domestic price dampening pressures due to foreign import competition.

a residual to ensure that the steady-state cost is zero. In this specification, the adjustment costs kick in when the change of investment from its steady state is above 5 percentage points.

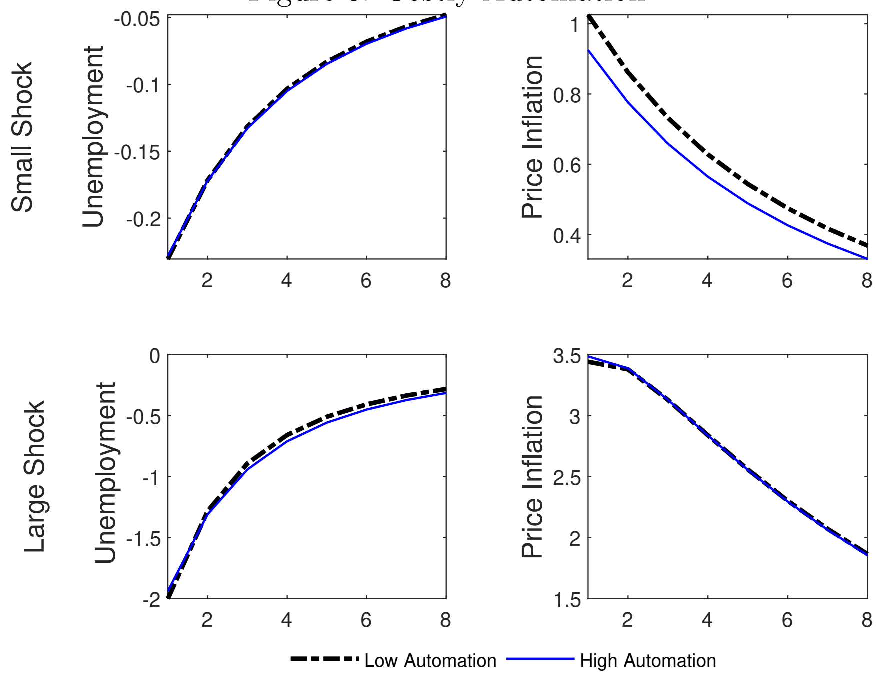
The adjustment cost function implies that the price of machines rises substantially when robot production ramps up. As the demand of investment surges, the large increase in the magnitude of the adjustment cost hikes up the price of machines. A higher price of machines implies that for a set of producers the outside option of automation ceases to be profitable, leading to a drop in the automation cut-off, and a surge in the relative measure of labor firms. Workers exploit this situation by negotiation higher wages, which are passed into prices. In this setting, large expansionary demand shocks that reduce substantially unemployment are accompanied by a spike in wages and prices.[21] In other words, when boosting automation is costly, the threat of robot adoption is no longer effective in curtailing workers' bargaining power amidst large expansionary shock, leading to the resurgence of a steep Phillips curve.

The analysis of the implications of this model extension is challenged by the uncertainty on how to discipline the cost function and the size of the shock hitting the economy. Thus, although this analysis is quantitative in nature, we interpret it as a proof-of-concept illustration of how costly robot adoption can account for a steep Phillips curve amidst large expansionary shocks. To do so, we start by setting the costs parameters to $\delta = 0.0015$ and $\varrho = 100$ to capture the idea that the adjustment costs are negligible when the change in investment is limited, but then any variation in investment from its steady state which is above 5% leads to a convexly increasing cost. This parametrization implies that a 7 percentage point increase in investment above its steady state level implies a cost which is three times as large as that associated to a 6 percentage point increase. In this way, we can evaluate the implications of a costly ramping-up of automation. We then consider the response of the low automation and high automation economies featuring costly robot adoption to two expansionary demand shocks that only differ in their size: a small shock that makes unemployment to decrease by 0.25 percentage points, and a large shock that makes unemployment to decrease by 2 percentage points.

The results of the exercise are reported in Figure 6. The graphs at the top show the response of unemployment and inflation under the small shock realiza-

[21] When the price of robots hikes up, also the low-efficiency firms that keep operating using robots after the shock face an increase in marginal costs, putting further upward pressure on prices.

Figure 6: Costly Automation



Note: Impulse responses of unemployment gap (in percentage points) and price inflation (in annualized percentage points) to a small and large demand shocks designed to generate similar responses in unemployment in economies with high and low degrees of automation.

tion, whereas the two graphs at the bottom indicate the behavior of the same two variables following the large shock realization. The responses of unemployment are normalized to be the same in both the low and high automation scenarios. When the economy is hit by a small positive expansionary shock, inflation surges relatively less in the high automation economy, confirming our previous results on the fact that robot adoption flattens the price Phillips curve. However, when the size of the shock is large, there is no difference whatsoever in the response of inflation in the low automation and high automation economies. Thus, while an increase in automation flattens the price Phillips curve when the size of the shock is small, automation does not influence at all the inflation sensitivity to unemployment amidst large shock, leading to the resurgence of a steep Phillips curve.

From this perspective, our model can rationalize not only the muted responsiveness of inflation to unemployment observed in the post 1980's, but also the sudden spike in inflation that has characterized the post-Covid recovery. Interestingly, the way in which our model accounts for the lack of effect of automation on the slope of the Phillips curve is also consistent with some recent empirical evidence of Autor et al. (2023), showing that the increases in wage post-Covid have been stronger for low educated and low income workers, whose wages have been compressed during the past decades. That is consistent with the implications of our analysis: when ramping up robot adoption is costly, there is a relatively lower degree of worker replacement, such that we observe a relatively higher share of low-efficiency firms producing employing low-wage workers.

5 Conclusion

How does robot adoption influence inflation dynamics? We show empirically, theoretically, and quantitatively that economies characterized by a higher degree of automation experience a lower sensitivity of inflation to movements in unemployment. As such, the substantial increase in the use of robots and other forms of automation in production processes experienced in most advanced economies in the last decades may be associated with the missing inflation observed during the same period, when inflationary pressures did not materialize despite the fluctuations observed in unemployment rates.

We first leverage a panel of nontradable goods inflation, wage inflation, unemployment rate and robot adoption at the U.S. MSA level to uncover the causal effect of automation on the inflation sensitivity to automation. We find that robot adoption decouples inflation from unemployment, and this effect is also economically relevant: an increase in robot adoption by one standard deviation reduces the sensitivity of prince inflation and wage inflation to unemployment by 17% and 9%, respectively. Overall, our empirical analysis uncovers three novel findings relating automation to inflation dynamics: robot adoption reduces (*i*) the sensitivity of price inflation to unemployment, (*ii*) the sensitivity of wage inflation to unemployment, and (*iii*) the pass-through from wages to prices.

To rational these facts, we extend a standard New Keynesian model with two key augmented features: search frictions in the labor market and the possibility of robot adoption. In this economy, increasing automation to an amount that replicates the variation in robot penetration across MSAs leads to a reduction in the slope of the price and wage Phillips curve by 14% and 13%. Thus, the model accounts for 82% of the flattening of the price Phillips curve estimated in our data, while overstates the flattening in the wage Phillips curve. Finally, we show that when ramping-up automation is costly, the threat that robots pose to workers' bargaining power crucially depend on the size of the shock realizations. When facing a small expansionary shock, firms can purchase additional machines without facing a sharp increase in robot prices, and thus gain an upper hand on wage negotiations. Instead, amidst large expansionary shocks, the adjustment cost translates into higher machine prices, so that the threat of robot adoption is no longer effective in curtailing workers' bargaining power. Consequently, automation does not affect the slope of the Phillips curve amidst large expansionary shocks, leading to the resurgence of a steep relationship.

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A Empirical Evidence: Robustness

This section evaluates the robustness of our empirical findings as well as corroborates the validity of our identification strategy by reporting a comprehensive battery of checks. Specifically, we consider to what extent our findings keep holding when accounting for the role of potential alternative explanations for the decoupling of inflation and unemployment dynamics, and when including variables which could be highly correlated (across states and over time) with the surge of automation. To do so, we estimate a sequence of additional regressions in which we introduce each time a new key potential confounding factor and we explicitly control for both its local lagged level and its interaction with the local unemployment rate. In this way, we can evaluate whether the effect of automation on inflation dynamics keeps holding above and beyond the interaction that unemployment may have with other MSA-level characteristics.

Our first set of potential alternative explanations relate to heterogeneity in demographic characteristics across metropolitan areas. To address this set of variables, we merge our data with information from the Current Population Survey (CPS) of the U.S. Census Bureau, and we compute for each metropolitan area the following characteristics: (*i*) the share of young people in total population, defined as the share of individuals whose age is below 30 years, (*ii*) the share of old people in total population, defined as the share of individuals whose age is above 60 years, (*iii*) the female labor market participation, (*iv*) the black people labor market participation, (*v*) the asian people labor market participation, (*vi*) the share of individuals with low educational attainments, defined as those people who have attended at most until the tenth grade, (*vii*) the overall labor market participation, and (*viii*) the average marginal propensity to consume (MPC). To compute the latter, we follow Herreño and Pedemonte (2022) and combine the estimate of the MPC by demographic characteristics derived by Patterson (2023) with the share of each of this characteristic in each metropolitan area in each year of our sample. Overall, merging our initial data with the CPS information slightly reduces the total number of observations in our panel, from 3,205 to 2,270.

We then report the results of extending our baseline regression to include the lagged value of each of the above demographic characteristics — one at a time — both as its lagged values and its interaction with the unemployment rate in Table A. Overall, we find that the role of automation is always highly statistically significant and rather constant across the different specifications. These

Table A.1: Robot Adoption and Inflation across MSAs - The Role of Demographics

	Dependent Variable: $\pi_{N,i,t}$							
	Young People	Old People	Female Labor Particip.	Black Labor Particip.	Asian Labor Particip.	Low Education	Labor Force Particip.	MPC
	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)	IV (8)
$u_{i,t-1}$	-0.5942***	-0.6016***	-0.5997***	-0.5927***	-0.5889***	-0.6009***	-0.6039***	-0.6001***
	(0.1511)	(0.1500)	(0.1381)	(0.1483)	(0.1463)	(0.1491)	(0.1488)	(0.1498)
$u_{i,t-1} \times (m_{i,t-1} - \bar{m})$	0.0140***	0.0140***	0.0143***	0.0138***	0.0140***	0.0140***	0.0136***	0.0140***
	(0.0051)	(0.0051)	(0.0051)	(0.0050)	(0.0051)	(0.0051)	(0.0050)	(0.0051)
$u_{i,t-1} \times \left(VAR_{i,t-1} - V\bar{A}R\right)$	-0.0402	-0.0326	-0.1496	-0.0672	0.1181	-0.0699	0.1975**	-0.1412
	(0.0804)	(0.0685)	(0.1127)	(0.0585)	(0.1485)	(0.0858)	(0.0806)	(0.2669)
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
MSA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
N. Observations	2,270	2,270	2,270	2,270	2,270	2,270	2,270	2,270

Note: The table reports the estimates of panel regressions similar to that of Table 1 with the difference that we also include the interaction of the unemployment rate with a set of potential confounding factors one at a time, a term we refer to as $u_{i,t-1} \times \left(VAR_{i,t-1} - V\bar{A}R\right)$, where $VAR_{i,t-1}$ is the value that each of this additional confounding factors take in metropolitan area i at year t, and $V\bar{A}R$ is the associated average value in the sample. In all columns, the dependent variable is the non-tradables good inflation rate, $\pi_{N,i,t}$, and all cases are estimated with IV methods, in which the unemployment rate is instrumented with a shift-share variable that captures tradeable demand spillovers, and the robot-adoption variable is instrumented with the industry-level robot penetration in a pool of European countries. All regressions also include the lagged value of the robot-adoption variable, $m_{i,t-1}$, the lagged value of the confounding variable used in the interaction term, $VAR_{i,t-1}$, the relative price of non-tradable goods, $p_{N,i,t-1}$, as well as year and MSA fixed effects. Column (1) considers the role of the share of young people in total population, defined as those below 30 years old, Column (2) considers the role of the share of old people in total population, defined as those above 60 years old, Column (3) considers the role of the female labor participation, Column (4) considers the role of the labor participation of black workers, Column (5) considers the role of the labor participation of asian workers, Column (6) considers the share of workers with low educational attainments, defined as those workers who have attended school up to grade 10, Column (7) considers the role of the labor participation of all workers, and Column (8) considers the role of workers marginal propensity to consume. Double-clustered standard errors are reported in brackets. *** and ** indicate statistical significance at the 1% and 5%, respectively.

results also suggest our baseline setting does not capture the relationship that automation has with the aging labor force (Basso and Jimeno, 2021; Acemoglu and Restrepo, 2022), and in turn the effect of the aging population on long-run inflation dynamics (Aksoy et al., 2019). The effect of automation holds also above and beyond the way in which differences in the MPC across metropolitan areas modulate the transmission of monetary policy, as documented by Herreño and Pedemonte (2022).

The second set of confounding factors we consider is related to the heterogeneous variations in the content of occupations across metropolitan areas. Indeed, robot adoption has lead to a decline in both routine and manual occupations (Acemoglu and Restrepo, 2018, 2020a, 2020b), a phenomenon which is intrinsically related to the job polarization emphasized by Autor et al. (2013). We evaluate the role of changes in the occupational structure as Siena and Zago (2022) shows that the disappearance of routine and manual occupations is a potential explanation for the flattening of the price Phillips curve in the early 2000s. To show that the effect of automation on inflation dynamics holds above and beyond that of job polarization, we merge our data with the information on occupations provided by the CPS, and the assignment of these occupations to manual, routine, and abstract, as well as their offshorable content, all of which come from Autor et al. (2013). We then report the results of extending our baseline regression to include the lagged value of each of the above occupational characteristics — one at a time — both as its lagged values and its interaction with the unemployment rate in Table A. Again, we find that although the occupation offshorability also leads to a flattening of the price Phillips curve, the effect of automation on inflation dynamics holds even when explicitly controlling for the time-variation in the occupational structure across metropolitan areas.

Finally, the third set of potential alternative explanations relates to the key role that foreign import competition has had on the changes in inflation dynamics in the pre-Covid and the post-Covid periods (Forbes, 2019; Heise et al., 2022, 2023). Specifically, we consider to what extent the effect of automation on inflation could hold when including in our regressions the role of imports from China and Mexico, which are the two countries which have been providing the largest competition threats to U.S. products. To do so, we closely follow the steps of Autor et al. (2013): we get import data from the UN Comtrade on imports from China and Mexico at the 6 digit Harmonized System product level, we convert this information into 1987 four-digit SIC codes, and finally transform the infor-

Table A.2: Robot Adoption and Inflation across MSAs - The Role of Occupations

	Dependent Variable: $\pi_{N,i,t}$			
	Abstract Occupations	Routine Occupations	Manual Occupations	Offshorable Occupations
	IV (1)	IV (2)	IV (3)	IV (4)
$u_{i,t-1}$	-0.5888*** (0.1364)	-0.5842*** (0.1358)	-0.5921*** (0.1372)	-0.5928*** (0.1365)
$u_{i,t-1}\times$ $(m_{i,t-1} - \bar{m})$	0.0114*** (0.0044)	0.0125*** (0.0044)	0.0127*** (0.0044)	0.0124*** (0.0044)
$u_{i,t-1}\times$ $\left(VAR_{i,t-1} - V\bar{A}R\right)$	-0.0175 (0.0109)	0.0170 (0.0170)	0.0051 (0.0202)	0.0429* (0.0242)
Year Fixed Effects	✓	✓	✓	✓
MSA Fixed Effects	✓	✓	✓	✓
N. Observations	2,489	2,489	2,489	2,489

Note: The table reports the estimates of panel regressions similar to that of Table 1 with the difference that we also include the interaction of the unemployment rate with a set of potential confounding factors one at a time, a term we refer to as $u_{i,t-1} \times \left(VAR_{i,t-1} - V\bar{A}R\right)$, where $VAR_{i,t-1}$ is the value that each of this additional confounding factors take in metropolitan area i at year t, and $V\bar{A}R$ is the associated average value in the sample. In all columns, the dependent variable is the non-tradables good inflation rate, $\pi_{N,i,t}$, and all cases are estimated with IV methods, in which the unemployment rate is instrumented with a shift-share variable that captures tradeable demand spillovers, and the robot-adoption variable is instrumented with the industry-level robot penetration in a pool of European countries. All regressions also include the lagged value of the robot-adoption variable, $m_{i,t-1}$, the lagged value of the confounding variable used in the interaction term, $VAR_{i,t-1}$, the relative price of non-tradable goods, $p_{N,i,t-1}$, as well as year and MSA fixed effects. Column (1) considers the share of abstract occupations in total occupations, Column (2) considers the share of routine occupations in total occupations, Column (3) considers the share of manual occupations in total occupations, and Column (3) considers the share of offshorable occupations in total occupations. Double-clustered standard errors are reported in brackets. *** and ** indicate statistical significance at the 1% and 5%, respectively.

mation at the 1997 six-digit NAICS codes. We use the employment structure of each metropolitan area at the industry level to compute a time-varying measure of Chinese and Mexican import competition over the entire sample period, and merge it with our original data. We then report the results of extending our baseline regression to include the lagged value of each of the above imports variable — either the imports from China, or the imports from Mexico, or the sum imports from the two countries — both as its lagged values and its interaction with the unemployment rate in Table A. We find that although the total imports did flatten the price Phillips curve, the effect of automation on inflation dynamics hold above and beyond the time-variation in import competition across metropolitan areas. In fact, the estimations in column (3) in Table A imply that an increase in robot adoption by one standard deviation reduces the sensitivity of prince inflation by 19% (a slight increase relative to the baseline estimation) while an increase in import competition by one standard deviation reduces the sensitivity of prince inflation by 13%.

Table A.3: Robot Adoption and Inflation across MSAs - The Role of Import Competition

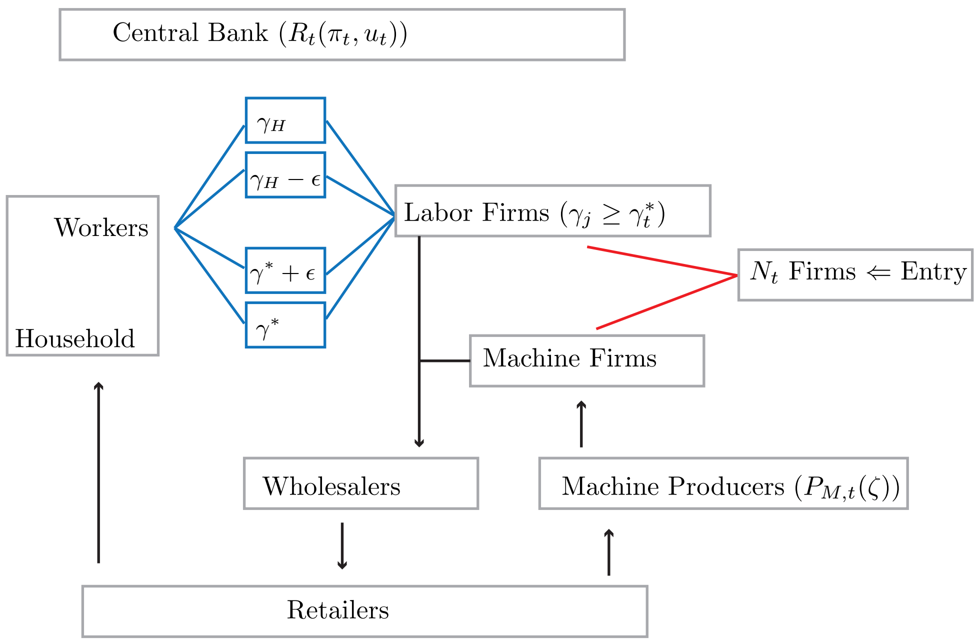
	Dependent Variable: $\pi_{N,i,t}$		
	Chinese Imports	Mexican Imports	Chinese & Mexican Imports
	IV	IV	IV
	(1)	(2)	(3)
$u_{i,t-1}$	-0.5687***	-0.7265***	-0.6056***
	(0.1399)	(0.2033)	(0.1549)
$u_{i,t-1}\times$ $(m_{i,t-1}-\bar{m})$	0.0063**	0.0105***	0.0077**
	(0.0032)	(0.0040)	(0.0044)
$u_{i,t-1}\times$ $\left(VAR_{i,t-1}-V\bar{A}R\right)$	0.0141	-0.8281	0.1812*
	(0.0675)	(0.5082)	(0.1011)
Year Fixed Effects	✓	✓	✓
MSA Fixed Effects	✓	✓	✓
N. Observations	3,526	3,526	3,526

Note: The table reports the estimates of panel regressions similar to that of Table 1 with the difference that we also include the interaction of the unemployment rate with a set of potential confounding factors one at a time, a term we refer to as $u_{i,t-1}\times\left(VAR_{i,t-1}-V\bar{A}R\right)$, where $VAR_{i,t-1}$ is the value that each of this additional confounding factors take in metropolitan area i at year t, and $V\bar{A}R$ is the associated average value in the sample. In all columns, the dependent variable is the non-tradables good inflation rate, $\pi_{N,i,t}$, and all cases are estimated with IV methods, in which the unemployment rate is instrumented with a shift-share variable that captures tradeable demand spillovers, and the robot-adoption variable is instrumented with the industry-level robot penetration in a pool of European countries. All regressions also include the lagged value of the robot-adoption variable, $m_{i,t-1}$, the lagged value of the confounding variable used in the interaction term, $VAR_{i,t-1}$, the relative price of non-tradable goods, $p_{N,i,t-1}$, as well as year and MSA fixed effects. Column (1) considers the share of abstract occupations in total occupations, Column (2) considers the share of routine occupations in total occupations, Column (3) considers the share of manual occupations in total occupations, and Column (3) considers the share of offshorable occupations in total occupations. Double-clustered standard errors are reported in brackets. *** and ** indicate statistical significance at the 1% and 5%, respectively.

B Further Details on the Model

This section provides additional details on the baseline model. We start by showing a graphical representation of the structure of the economy and the interplay between the different agents in Figure B.1. Then, Section B.1 reports the derivation of the wage setting of labor firms, as well as the value of labor firms, and how it increases as a function of the efficiency in employing the labor technology. Section B.2 describes the full set of equilibrium conditions, Section B.3 shows the characterization of the price Phillips curve, and Section B.4 details the characterization of the wage-to-price pass-through.

Figure B.1: The Structure of the Model



Note: This figure gives a graphical representation of the structure of the model economy.

B.1 Wage Setting and The Value of Labor Firms

Equation (11) shows the wage posted by firms in sub-market ω increases with both the level of labor efficiency and the price of producer goods, multiplied by the inverse of the elasticity of matches to vacancies. In other words, $P_{P,t}\gamma_j$ is the total value of production of a successful match, and this surplus is split among workers and firms as a function of the matching elasticity with respect to vacancies. Hereafter, we describe the derivation of the wage setting problem.

Specifically, if we combine workers payoff from searching in any sub-market of in Equation (6), with both the probability to find a job of Equation (4) and the probability to fill a vacancy of Equation (5), we can determine the probability of filling a vacancy as a function of the posted wage. In this way, we get the following condition:

$$q_{\omega,t}(\theta_{\omega,t}) = \xi^{\frac{1}{\eta}} \left(\frac{W_{\omega,t}}{J_t} \right)^{\frac{1-\eta}{\eta}}. \tag{B.1}$$

The wage setting problem can then be expressed as the value of the wage to be posted in each sub-market ω such that it maximizes the value of the labor with efficiency γ_j, $V_{L,t}(\gamma_j)$, subject to the way in which the level of the offered wage and workers' searching value influences the probability to fill a vacancy, that is

$$\max_{W_{\omega,t}} \quad V_{L,t}(\gamma_j) \equiv q_{\omega,t}(\theta_{\omega,t}) \left[P_{P,t}\gamma_j - W_{\omega,t} \right] - \kappa \tag{B.2}$$

$$\text{s.t.} \quad q_{\omega,t}(\theta_{\omega,t}) = \xi^{\frac{1}{\eta}} \left(\frac{W_{\omega,t}}{J_t} \right)^{\frac{1-\eta}{\eta}}. \tag{B.3}$$

Optimality then implies that the optimal wage offered in sub-market ω equals

$$W_{\omega,t} = P_{P,t}\gamma_j(1-\eta). \tag{B.4}$$

Finally, we can substitute the expression of the vacancy filling probability of Equation (B.1) and the optimal condition of wages in Equation (B.4) within the value of labor firms of Equation (B.2), to redefine the value of a labor firm with efficiency γ_j as

$$V_{L,t}(\gamma_j) = \xi^{\frac{1}{\eta}} \eta (1-\eta)^{\frac{1-\eta}{\eta}} J_t^{\frac{\eta-1}{\eta}} \left[P_{P,t}\gamma_j \right]^{\frac{1}{\eta}} - \kappa. \tag{B.5}$$

The latter condition clearly highlights that the value of labor firms increase in the level of their efficiency γ_j in the empirically relevant case in which $\eta < 1$. This property is then key in defining the automation threshold: since the value of robot firms does not vary with their labor efficiency levels, while that of labor firms does, there exist a cut-off point $\gamma_t^{\star}$ such that $V_{L,t}(\gamma_t^{\star}) = V_{M,t}$.

B.2 Equilibrium Conditions

To describe the entire set of equilibrium conditions of the model, let us first define the auxiliary variable $\vartheta \equiv \xi^{\frac{1}{\eta}}(1-\eta)^{\frac{1-\eta}{\eta}}$, as well as the real cost of entry (i.e., the nominal cost divided by the price of the final good), $\tilde{\kappa} \equiv \kappa/P_t$, and the relative price of machines, $q_{M,t} \equiv P_{M,t}/P_t$. Then, the equilibrium conditions are

$$U_{C,t} = \beta \mathbb{E}_t \left[U_{C,t+1} R_t / \pi_{t+1} \right], \tag{B.6}$$

$$Y_t = C_t + I_t + \frac{\phi}{2}(\pi_t - 1)^2 (C_t + I_t), \tag{B.7}$$

$$(1-\epsilon)(C_t + I_t) + \epsilon \left(\frac{P_{P,t}}{P_t} \right) (C_t + I_t) - \phi(\pi_t - 1)\pi_t (C_t + I_t) + \dots$$

$$\dots + \beta \mathbb{E} \left[\frac{U_{C,t+1}}{U_{C,t}} \phi(\pi_{t+1} - 1)\pi_{t+1}(C_{t+1} + I_{t+1}) \right] = 0, \tag{B.8}$$

$$q_{M,t} \Xi_t \int_{\gamma_M}^{\gamma_t^\star} f(\gamma) d\gamma = I_t, \tag{B.9}$$

$$\gamma_M \frac{P_{P,t}}{P_t} - q_{M,t} = \vartheta \left(\frac{J_t}{P_t} \right)^{\frac{\eta-1}{\eta}} \left(\frac{P_{P,t}}{P_t} \gamma_t^\star \right)^{\frac{1}{\eta}}, \tag{B.10}$$

$$\int_{\gamma_M}^{\gamma_t^\star} \left(\frac{P_{P,t}}{P_t} \gamma_M - q_{M,t} - \tilde{\kappa} \right) f(\gamma) d\gamma + \dots$$

$$\dots + \int_{\gamma_t^\star}^{\gamma_H} \left[\vartheta \left(\frac{J_t}{P_t} \right)^{\frac{\eta-1}{\eta}} \left(\frac{P_{P,t}}{P_t} \gamma \right)^{\frac{1}{\eta}} - \tilde{\kappa} \right] f(\gamma) d\gamma = 0, \tag{B.11}$$

$$\Xi_t \left[\int_{\gamma_M}^{\gamma_t^\star} \gamma_M f(\gamma) d\gamma + \int_{\gamma_t^*}^{\infty} \xi^{\frac{1}{\eta}} (1-\eta)^{\frac{1-\eta}{\eta}} \left(\frac{J_t}{P_t} \right)^{\frac{\eta-1}{\eta}} \times \dots \right.$$

$$\left. \dots \times \left(\frac{P_{P,t}}{P_t} \gamma \right)^{\frac{1-\eta}{\eta}} \gamma f(\gamma) d\gamma \right] = Y_t, \tag{B.12}$$

$$\Xi_t \int_{\gamma_t^\star}^{\gamma_H} \xi^{\frac{1}{\eta}} \left(\frac{J_t}{P_t} \right)^{-\frac{1}{\eta}} \left[\frac{P_{P,t}}{P_t} \gamma (1-\eta) \right]^{1/\eta} f(\gamma) d\gamma = N_t, \tag{B.13}$$

$$N_t u_t = N_t - \Xi_t \left\{ \int_{\gamma_t^\star}^{\gamma_H} \xi^{\frac{1}{\eta}} \left(\frac{J_t}{P_t} \right)^{\frac{\eta-1}{\eta}} \left[\frac{P_{P,t}}{P_t} \gamma (1-\eta) \right]^{\frac{1-\eta}{\eta}} f(\gamma) d\gamma \right\}, \tag{B.14}$$

$$N_t = \frac{J_t}{P_t} \frac{U_{C,t}}{\lambda_H}. \tag{B.15}$$

If we define the real value of searching for an individual as $\tilde{J}_t \equiv J_t/P_t$, the relative price of producers' goods as $q_{P,t} \equiv P_{P,t}/P_t$, and given the functional form for the distribution of labor efficiency, $f(\gamma) = \frac{\alpha \gamma_M^\alpha \gamma^{-\alpha-1}}{1-\gamma_M^\alpha \gamma_H^{-\alpha}}$, then the equilibrium conditions become

$$U_{C,t} = \beta \mathbb{E}_t \left[U_{C,t+1} R_t / \pi_{t+1} \right], \tag{B.16}$$

$$Y_t = C_t + I_t + \frac{\phi}{2}(\pi_t - 1)^2 (C_t + I_t), \tag{B.17}$$

$$(1-\epsilon)(C_t + I_t) + \epsilon q_{P,t}(C_t + I_t) - \phi(\pi_t - 1)\pi_t (C_t + I_t) + \dots$$

$$\dots + \beta \mathbb{E}_t \left[\frac{U_{C,t+1}}{U_{C,t}} \phi(\pi_{t+1} - 1)\pi_{t+1}(C_{t+1} + I_{t+1}) \right] = 0, \tag{B.18}$$

$$q_{M,t} \Xi_t \frac{1 - \gamma_M^{\alpha} \gamma_t^{\star\,-\alpha}}{1 - \gamma_M^{\alpha} \gamma_H^{-\alpha}} = I_t, \tag{B.19}$$

$$\gamma_M q_{P,t} - q_{M,t} = \vartheta \eta \tilde{J}_t^{\frac{\eta-1}{\eta}} \left(q_{P,t} \gamma_t^{\star} \right)^{1/\eta}, \tag{B.20}$$

$$\tilde{\kappa} \left(1 - \gamma_M^{\alpha} \gamma_H^{-\alpha} \right) = \left(1 - \gamma_M^{\alpha} \gamma_t^{\star\,-\alpha} \right) \left(q_{P,t} \gamma_M - q_{M,t} \right) + \dots$$

$$\dots + \left(\vartheta \eta \tilde{J}_t^{\frac{\eta-1}{\eta}} q_{P,t}^{\frac{1}{\eta}} \right) \frac{\alpha\eta}{\alpha\eta - 1} \left(\frac{\gamma_M^{\alpha}}{\gamma_t^{\star\,\alpha - 1/\eta}} - \frac{\gamma_M^{\alpha}}{\gamma_H^{\alpha - 1/\eta}} \right), \tag{B.21}$$

$$\gamma_M - \frac{\gamma_M^{\alpha+1}}{\gamma_t^{\star\,\alpha}} + \vartheta \tilde{J}_t^{\frac{\eta-1}{\eta}} q_{P,t}^{\frac{\eta-1}{\eta}} \frac{\alpha\eta}{\alpha\eta - 1} \gamma_M^{\alpha} \left(\gamma_t^{\star\,\frac{1-\eta\alpha}{\eta}} - \gamma_H^{\frac{1-\eta\alpha}{\eta}} \right) = \dots$$

$$\dots = \frac{Y_t}{\Xi_t} \left(1 - \gamma_M^{\alpha} \gamma_H^{-\alpha} \right), \tag{B.22}$$

$$\Xi_t \frac{\xi^{\frac{1}{\eta}} (1-\eta)^{\frac{1}{\eta}}}{1 - \gamma_M^{\alpha} \gamma_H^{-\alpha}} \tilde{J}_t^{-\frac{1}{\eta}} q_{P,t}^{\frac{1}{\eta}} \frac{\alpha\eta}{\alpha\eta - 1} \gamma_M^{\alpha} \left(\gamma_t^{\star\,-\alpha + 1/\eta} - \gamma_H^{-\alpha + 1/\eta} \right) = N_t, \tag{B.23}$$

$$N_t u_t = N_t - \frac{\vartheta \tilde{J}_t^{\frac{\eta-1}{\eta}} q_{P,t}^{\frac{1-\eta}{\eta}}}{1 - \gamma_M^{\alpha} \gamma_H^{-\alpha}} \times \dots$$

$$\dots \times \frac{\alpha\eta}{\alpha\eta - 1 + \eta} \Xi_t \gamma_M^{\alpha} \left[\gamma_t^{\star\,-\alpha + (1-\eta)/\eta} - \gamma_H^{-\alpha + (1-\eta)/\eta} \right], \tag{B.24}$$

$$N_t = \tilde{J}_t U_{C,t} / \lambda_H. \tag{B.25}$$

We can also obtain the average real wage, $w_t \equiv W_t / P_t$, as follows:

$$\begin{aligned} w_t &= \frac{\int_{\gamma_t^{\star}}^{\gamma_H} q_{P,t} \gamma (1-\eta) \frac{\alpha \gamma_M^{\alpha} \gamma^{-\alpha-1}}{1 - \gamma_M^{\alpha} \gamma_H^{-\alpha}} d\gamma}{\int_{\gamma_t^{\star}}^{\gamma_H} \frac{\alpha \gamma_M^{\alpha} \gamma^{-\alpha-1}}{1 - \gamma_M^{\alpha} \gamma_H^{-\alpha}} d\gamma} = \dots \\ \dots &= q_{P,t} (1-\eta) \frac{\alpha}{\alpha - 1} \frac{\gamma_t^{\star\,1-\alpha} - \gamma_H^{1-\alpha}}{\gamma_t^{\star\,-\alpha} - \gamma_H^{-\alpha}}. \end{aligned} \tag{B.26}$$

Then, combining Equations (B.23) and (B.24), we have that at steady state the real value that individuals have in searching for a job equals

$$\bar{\tilde{J}} = \frac{(1-\bar{u})(1-\eta)\bar{p_P}\left(\gamma_t^{\star\,-\alpha+1/\eta} - \gamma_H^{-\alpha+1/\eta}\right)}{\left[\gamma_t^{\star\,-\alpha+(1-\eta)/\eta} - \gamma_H^{-\alpha+(1-\eta)/\eta}\right]}\frac{\alpha\eta-1+\eta}{\alpha\eta-1}. \tag{B.27}$$

Given the auxiliary variable $\varpi_1 \equiv \bar{q_P}\gamma_M - \bar{q}_M$, log-linearizing the equilibrium conditions around the steady state gives

$$-\sigma\hat{C}_t = \beta\hat{R}_t\mathbb{E}_t\left[-\sigma\hat{C}_{t+1} - \hat{\pi}_{t+1}\right], \tag{B.28}$$

$$\hat{Y}_t = \frac{\bar{C}}{\bar{Y}}\hat{C}_t + \frac{\bar{I}}{\bar{Y}}\hat{I}_t, \tag{B.29}$$

$$\hat{\pi}_t = \frac{\epsilon-1}{\phi}\widehat{q_{P,t}} + \beta\frac{\epsilon-1}{\phi}\mathbb{E}_t\left[\hat{\pi}_{t+1}\right], \tag{B.30}$$

$$\hat{\Xi}_t + \frac{\frac{\alpha\gamma_M^\alpha}{\bar{\gamma}^{\star\,\alpha}}}{1-\frac{\gamma_M^\alpha}{\bar{\gamma}^{\star\,\alpha}}}\widehat{\gamma_t^*} = \hat{I}_t, \tag{B.31}$$

$$(\varpi_{1,S} - \eta\bar{q_P}\gamma_M)\widehat{q_{P,t}} + \varpi_{1,S}(\eta-1)\hat{\tilde{J}}_t + \varpi_{1,S}\widehat{\gamma_t^\star} = 0, \tag{B.32}$$

$$\left\{\left[1-\left(\frac{\gamma_M}{\bar{\gamma}^\star}\right)^\alpha\right]\eta\bar{q_P}\gamma_M + \varpi_1\frac{\alpha\eta}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^\star}\right)^\alpha - \left(\frac{\gamma_M}{\gamma_H}\right)^\alpha\left(\frac{\gamma_H}{\bar{\gamma}^\star}\right)^{\frac{1}{\eta}}\right]\right\}\widehat{q_{P,t}} + \dots$$

$$\dots + \varpi_1\frac{\alpha\eta(\eta-1)}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^\star}\right)^\alpha - \left(\frac{\gamma_M}{\gamma_H}\right)^\alpha\left(\frac{\gamma_H}{\bar{\gamma}^\star}\right)^{\frac{1}{\eta}}\right]\hat{\tilde{J}}_t = 0, \tag{B.33}$$

$$\frac{\varpi_1}{\eta\bar{q_P}}\frac{\alpha\eta}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^\star}\right)^\alpha - \left(\frac{\gamma_M}{\gamma_H}\right)^\alpha\left(\frac{\gamma_H}{\bar{\gamma}^\star}\right)^{\frac{1}{\eta}}\right]\left(\frac{\eta-1}{\eta}\hat{\tilde{J}}_t + \frac{1-\eta}{\eta}\widehat{q_{P,t}}\right) + \dots$$

$$\dots + \left(\alpha\gamma_M - \frac{\varpi_1\alpha}{\eta\bar{q_P}}\right)\left(\frac{\gamma_M}{\bar{\gamma}^\star}\right)^\alpha\widehat{\gamma_t^\star} = (\hat{Y}_t - \hat{\Xi}_t)\frac{\bar{Y}\left(1-\gamma_M^\alpha\gamma_H^{-\alpha}\right)}{\bar{\Xi}}, \tag{B.34}$$

$$\hat{\Xi}_t - \frac{1}{\eta}\hat{\tilde{J}}_t + \frac{1}{\eta}\widehat{q_{P,t}} + \left[\left(\frac{1}{\eta}-\alpha\right)\frac{\bar{\gamma}^{\star\,-\alpha+1/\eta}}{\bar{\gamma}^{\star\,-\alpha+1/\eta} - \gamma_H^{-\alpha+1/\eta}}\right]\widehat{\gamma_t^\star} = \hat{L}_t, \tag{B.35}$$

$$\frac{\bar{u}}{1-\bar{u}}\hat{u}_t = \hat{L}_t - \hat{\Xi}_t - \frac{(\eta-1)}{\eta}\hat{\tilde{J}}_t - \frac{(1-\eta)}{\eta}\widehat{q_{P,t}} + \dots$$

$$\dots + \left[\left(\alpha - \frac{1-\eta}{\eta}\right)\frac{\bar{\gamma}^{\star\,-\alpha+(1-\eta)/\eta}}{\bar{\gamma}^{\star\,-\alpha+(1-\eta)/\eta} - \gamma_H^{-\alpha+(1-\eta)/\eta}}\right]\widehat{\gamma_t^\star}, \tag{B.36}$$

$$\hat{L}_t = \hat{\tilde{J}}_t - \hat{C}_t, \tag{B.37}$$

$$\hat{w}_t = \widehat{q_{P,t}} + (1-\alpha)\frac{\bar{\gamma}^{\star\,1-\alpha}}{\bar{\gamma}^{\star\,1-\alpha} - \gamma_H^{1-\alpha}}\widehat{\gamma_t^\star}. \tag{B.38}$$

B.3 Derivation of the price Phillips Curve

Section 4.2 establishes that automation alters the slope of the price Phillips curve such that a relative larger share of robot firm among producers lead to a flattening of the relationship between price inflation and unemployment. In this section, we provide the details on the derivation of the price Phillips curve.

Specifically, rearranging Equation (B.33) and using the definition of the auxiliary variable ϖ_1 yields the following condition:

$$\begin{aligned} \hat{\hat{J}}_t &= \frac{\left(1-\frac{\gamma_M^{\alpha}}{\bar{\gamma}^{\star\,\alpha}}\right)\eta\bar{q_P}\gamma_M + \varpi_1\frac{\alpha\eta}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha} - \left(\frac{\gamma_M}{\gamma_H}\right)^{\alpha}\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{\frac{1}{\eta}}\right]}{\varpi_1\frac{\alpha\eta(1-\eta)}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha} - \left(\frac{\gamma_M}{\gamma_H}\right)^{\alpha}\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{\frac{1}{\eta}}\right]}\widehat{q_{P,t}} = \dots \\ \dots &= \frac{1}{1-\eta}\left(\frac{\eta\bar{q_P}\gamma_M}{\varpi_1}\varpi_2 + 1\right)\widehat{q_{P,t}}. \end{aligned} \tag{B.39}$$

Similarly, rearranging Equation (B.35) leads to

$$\hat{\Xi}_t = \frac{1}{\eta}\hat{\hat{J}}_t - \frac{1}{\eta}\widehat{q_{P,t}} + \left[\left(\alpha - \frac{1}{\eta}\right)\frac{\bar{\gamma}^{\star\,-\alpha+1/\eta}}{\bar{\gamma}^{\star\,-\alpha+1/\eta} - \gamma_H^{-\alpha+1/\eta}}\right]\widehat{\gamma_t^{\star}} + \hat{L}_t. \tag{B.40}$$

Next, combining Equation (B.32) with Equation (B.39) gives

$$\begin{aligned} &(\varpi_1 - \eta\bar{q_P}\gamma_M)\widehat{q_{P,t}} + \varpi_1\widehat{\gamma_t^{\star}} + \dots \qquad \text{(B.41)} \\ \dots + \varpi_1(\eta-1)&\frac{\left\{\left[1-\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha}\right]\eta\bar{q_P}\gamma_M + \varpi_1\frac{\alpha\eta}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha} - \left(\frac{\gamma_M}{\gamma_H}\right)^{\alpha}\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{\frac{1}{\eta}}\right]\right\}}{\varpi_1\frac{\alpha\eta(1-\eta)}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha} - \left(\frac{\gamma_M}{\gamma_H}\right)^{\alpha}\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{\frac{1}{\eta}}\right]}\widehat{q_{P,t}} = 0, \end{aligned}$$

$$\begin{aligned} \widehat{\gamma_t^{\star}} &= \frac{\eta\bar{q_P}\gamma_M}{\omega_1}\left\{1 + \frac{1-\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha}}{\frac{\alpha\eta}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha} - \left(\frac{\gamma_M}{\gamma_H}\right)^{\alpha}\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{\frac{1}{\eta}}\right]}\right\}\widehat{q_{P,t}} = \dots \\ \dots &= \frac{\eta\bar{q_P}\gamma_M}{\omega_1}(1+\varpi_2)\widehat{q_{P,t}}. \end{aligned} \tag{B.42}$$

Let us define the set of structural parameters $\Theta = \{\eta, \gamma_M, \gamma_H, \alpha, \epsilon\}$. Then, combining Equations (B.39), (B.40) and (B.42) with Equation (B.36), and using Equation (B.27) while noting that at steady state the relative price of producers goods equals $\bar{q_P} = (\epsilon-1)/\epsilon$, we have that

$$
\begin{aligned}
\hat{u}_t &= \frac{1-\bar{u}}{\bar{u}}\left[\frac{1}{\eta}\widehat{q_{P,t}} - \hat{L}_t - \frac{1}{\eta}\hat{\tilde{J}}_t - \left[\left(\alpha - \frac{1}{\eta}\right)\frac{\bar{\gamma}^{\star\,-\alpha+1/\eta}}{\bar{\gamma}^{\star\,-\alpha+1/\eta} - \gamma_H^{-\alpha+1/\eta}}\right]\widehat{\gamma_t^{\star}} + \dots\right. \\
&\quad \dots + \left[\alpha - \left(\frac{1-\eta}{\eta}\right)\frac{\bar{\gamma}^{\star\,-\alpha+(1-\eta)/\eta}}{\bar{\gamma}^{\star\,-\alpha+(1-\eta)/\eta} - \gamma_H^{-\alpha+(1-\eta)/\eta}}\right]\widehat{\gamma_t^{\star}} - \dots \\
&\quad \left.\dots - \frac{(\eta-1)}{\eta}\hat{\tilde{J}}_t - \frac{(1-\eta)}{\eta}\widehat{q_{P,t}}\right] + \frac{1-\bar{u}}{\bar{u}}\hat{L}_t, \qquad \text{(B.43)}
\end{aligned}
$$

$$
\begin{aligned}
\hat{u}_t &= \frac{1-\bar{u}}{\bar{u}}\left\{ - \hat{\tilde{J}}_t + \widehat{q_{P,t}} + \dots \right. \qquad \text{(B.44)} \\
&\quad \left. \dots + \left[\frac{\left(\alpha - \frac{1-\eta}{\eta}\right)\bar{\gamma}^{\star\,-\alpha+(1-\eta)/\eta}}{\bar{\gamma}^{\star\,-\alpha+(1-\eta)/\eta} - \gamma_H^{-\alpha+(1-\eta)/\eta}} - \frac{\left(\alpha - \frac{1}{\eta}\right)\bar{\gamma}^{\star\,-\alpha+1/\eta}}{\bar{\gamma}^{\star\,-\alpha+1/\eta} - \gamma_H^{-\alpha+1/\eta}}\right]\widehat{\gamma_t^{\star}}\right\}, \\
\widehat{q_{P,t}} &= \frac{\bar{u}}{1-\bar{u}}\frac{1}{\left\{-\frac{\eta}{1-\eta} - \frac{\eta(\epsilon-1)\gamma_M}{\epsilon\omega_1}\left[\frac{1}{1-\eta}\varpi_2 - \varpi_3\left(1+\varpi_2\right)\right]\right\}}\hat{u}_t = \dots \\
&= \Psi(\bar{\gamma}^{\star};\Theta)\hat{u}_t, \qquad \text{(B.45)}
\end{aligned}
$$

where the auxiliary variables ϖ_1, ϖ_2, and ϖ_3 equal

$$
\begin{aligned}
\varpi_1 &= \xi\left[\eta\frac{\epsilon-1}{\epsilon}\right]^{\eta}\bar{\gamma}^{\star}/\left\{(1-\bar{u})\bar{\gamma}^{\star}\left[\frac{1-(\gamma_H/\bar{\gamma}^{\star})^{\frac{1}{\eta}-\alpha}}{1-(\gamma_H/\bar{\gamma}^{\star})^{\frac{(1-\eta)}{\eta}-\alpha}}\right]\left(1+\frac{\eta}{\alpha\eta-1}\right)\right\}^{1-\eta}, \\
\varpi_2 &= \left[1-\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha}\right]/\left\{\frac{\alpha\eta}{\alpha\eta-1}\left[\left(\frac{\gamma_M}{\bar{\gamma}^{\star}}\right)^{\alpha} - \left(\frac{\gamma_M}{\gamma_H}\right)^{\alpha}\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{1/\eta}\right]\right\}, \\
\varpi_3 &= \left(\alpha - \frac{1-\eta}{\eta}\right)\left[1-\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{\frac{(1-\eta)}{\eta}-\alpha}\right]^{-1} - \left(\alpha-\frac{1}{\eta}\right)\left[1-\left(\frac{\gamma_H}{\bar{\gamma}^{\star}}\right)^{\frac{1}{\eta}-\alpha}\right]^{-1}.
\end{aligned}
$$

If we denote by ${u^F}_t$ the level of unemployment in the counterfactual economy featuring flexible prices, the price Phillips curve can then be written as

$$
\hat{\pi}_t = \frac{\epsilon-1}{\phi}\Psi(\bar{\gamma}^{\star};\Theta)(\hat{\tilde{u}}_t - \hat{\tilde{u}}_t^F) + \mathbb{E}_t\left[\beta\frac{\epsilon-1}{\phi}\hat{\pi}_{t+1}\right], \qquad \text{(B.46)}
$$

where $\hat{\tilde{u}}_t = \frac{u_t - {u^F}_t}{\bar{u}}$ is defined as the deviation of unemployment level from its level under flexible prices, and $\hat{\tilde{u}}_t^F = \frac{u_t^F - \bar{u}}{\bar{u}}$ is the adjusted deviation of unemployment under flexible prices from its steady-state level.

B.4 Derivation of the Wage-to-Price Pass-Through

Section 4.3 expands the analysis of Section Section 4.2 to establish that automation affects not only the slope of the price Phillips curve, but also the pass-through from wages into prices. In what follows, we show the derivation of the wage-to-price pass-through, defined as the relationship that links changes in the average real wage, w_t, and changes in wholesalers' real marginal cost, $q_{P,t}$. We can then rearrange Equation (B.38) to uncover the pass-through as follows

$$\hat{w}_t = \widehat{q_{P,t}} + \frac{\bar{\gamma}^{\star\,-\alpha}\gamma_H^{-\alpha}\left[1-\alpha+\alpha(\gamma_H/\bar{\gamma}^\star)\right]}{\left(\bar{\gamma}^{\star\,-\alpha}-\gamma_H^{-\alpha}\right)^2}\widehat{\gamma_t^\star} \tag{B.47}$$

$$= \widehat{q_{P,t}} + \frac{\bar{\gamma}^{\star\,-\alpha}\gamma_H^{-\alpha}\left[1-\alpha+\alpha(\gamma_H/\bar{\gamma}^\star)\right]}{\left(\bar{\gamma}^{\star\,-\alpha}-\gamma_H^{-\alpha}\right)^2}\frac{\eta\bar{q_P}\gamma_M}{\omega_1}\left(1+\varpi_2\right)\widehat{q_{P,t}} \tag{B.48}$$

$$\frac{1}{1+\frac{\bar{\gamma}^{\star\,-\alpha}\gamma_H^{-\alpha}\left[1-\alpha+\alpha(\gamma_H/\bar{\gamma}^\star)\right]}{\left(\bar{\gamma}^{\star\,-\alpha}-\gamma_H^{-\alpha}\right)^2}\frac{\eta\bar{q_P}\gamma_M}{\omega_1}\left(1+\varpi_2\right)}\hat{w}_t. \tag{B.49}$$

Consequently, we have the final relationship between changes in wholesalers' marginal costs and changes in the average real wage as

$$\widehat{q_{P,t}} = \Upsilon(\bar{\gamma}^\star;\Theta)\hat{w}_t, \tag{B.50}$$

where the variable $\Upsilon(\bar{\gamma}^\star;\Theta)$ captures the wage-to-price pass-through and is defined as

$$\Upsilon(\bar{\gamma}^\star;\Theta) = \left\{1+\frac{\bar{\gamma}^{\star\,-\alpha}\gamma_H^{-\alpha}\left[1-\alpha+\alpha(\gamma_H/\bar{\gamma}^\star)\right]}{\left(\bar{\gamma}^{\star\,-\alpha}-\gamma_H^{-\alpha}\right)^2}\frac{\eta\bar{q_P}\gamma_M}{\omega_1}\left(1+\varpi_2\right)\right\}^{-1}. \tag{B.51}$$

C Further Results of the Model

Section 4.5 reports the responses of unemployment, price inflation, the average wage, the wage-to-price pass-through, the number of firms, and the automation threshold in the low and high automation economies to an expansionary consumer demand shock $\varepsilon_{\Omega,t}$ that reduces unemployment by 1 percentage point.

In this section, we study the robustness of our findings by evaluating the response of the same set of variable in the low and high automation economies produced by two alternative sources of exogenous uncertainty. In the first case, we consider a monetary policy shock. Specifically, we alter the Taylor rule of Equation (33) by adding the monetary policy shock $\varepsilon_{R,t}$ as follows

$$R_t/\bar{R} = \left[R_{t-1}/\bar{R}\right]^{\psi_R} \left[(1+\pi_t)^{\psi_\pi} \left(u_t/u_t^F\right)^{\psi_u}\right]^{1-\psi_R} + \varepsilon_{R,t}. \tag{C.1}$$

We then compare the responses to an expansionary monetary policy shock of the six key variables by equalizing the response of unemployment in the two low and high automation economies, such that on impact unemployment drops by one percentage point. We report the results of this exercise in Figure C.1, which confirm the patterns derived by the responses to the consumer demand shock. An expansionary demand shock leads to price inflation, wages, and the wage-to-price pass-through to surge, coupled with an increase in both the total number of firms and the automation cut-off, so that the measure of labor firms raises both in relative and absolute terms.

However, the low automation economy features a much more muted response of price inflation: the impact response goes down by 13%, from 9.1 to 7.96 percentage points. In other words, the quantitative reduction in the inflation responsiveness due to automation is exactly the same for the case of monetary policy shocks or for the consumer demand shocks. As for the case of the preference shock, automation also leads to a reduction in the wage response as well as in the wage-to-price pass-through.

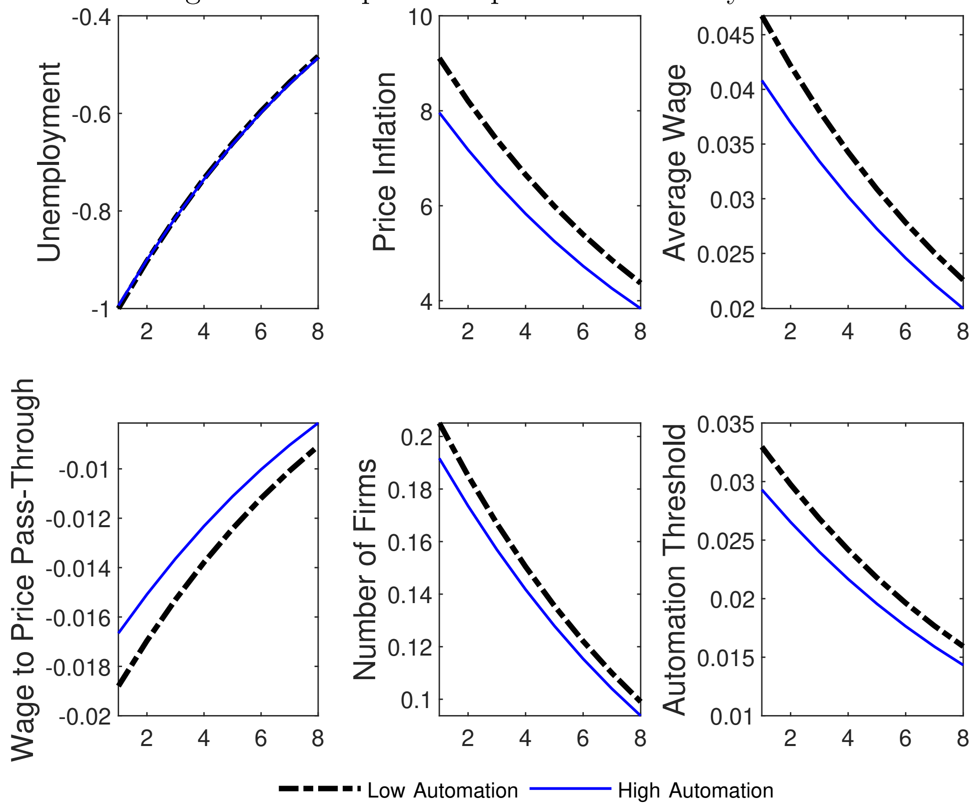
In the second case, we consider the effect of a productivity shock. Specifically, we alter the wholesalers' technology of Equation (18) as follows

$$Y_{i,t} = A_t Z_{i,t}, \tag{C.2}$$

where A_t is the level of productivity, whose logarithm follows the first-order autoregressive process

$$\log A_t = \rho_A \log A_{t-1} + \varepsilon_{A,t}, \tag{C.3}$$

Figure C.1: Impulse Responses - Monetary Shock



Note: Impulse responses of the unemployment rate (in percentage points), price inflation (in percentage points, annualized), average wage, the wage-to-price pass-through, number of firms and the automation cut-off point (γ^*) to an expansionary monetary policy shock designed to generate similar responses in unemployment in economies with high and low degrees of automation.

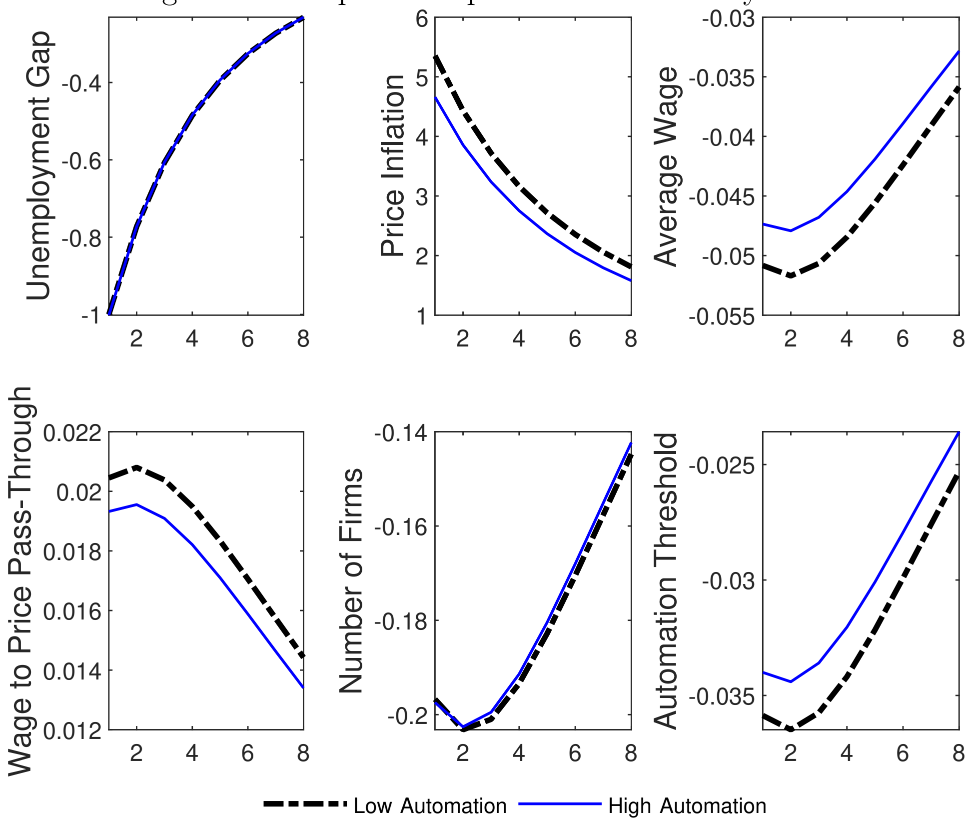
in which ρ_A captures the persistence of the process, and $\varepsilon_{A,t}$ is the productivity shock. We set the persistence to $\rho_A = 0.9$ so to generate exactly the same autocorrelation patterns for the shock process as those associated with the consumer demand process of Equation (30).

As in the previous case, we compare the responses to a contractionary productivity shock of the six key variables (looking in this case at the unemployment gap rather than the unemployment rate) by equalizing the response of the unemployment gap in the two low and high automation economies, such that on impact the unemployment gap drops by one percentage point.[22] We report the results in Figure C.2. Again, we find that a productivity shock reducing the unemployment gap leads to a surge in inflation, and this happens to a lower extent in the high automation economy. When automation surges, also the drop in wages

[22] A contractionary productivity shock raises the unemployment rate but it does so to a relatively lower extent than in the model specification with flexible prices. As a result, the unemployment gap goes down.

is more muted. The quantitative implications of automation on the decoupling of inflation and unemployment in the aftermath of a productivity shock equals to those derived under the preference shock: the impact response goes down by 13%, from 5.35 to 4.66 percentage points.

Figure C.2: Impulse Responses - Productivity Shock



Note: Impulse responses of the unemployment rate (in percentage points), price inflation (in percentage points, annualized), average wage, the wage-to-price pass-through, number of firms and the automation cut-off point (γ^*) to a contractionary productivity shock designed to generate similar responses in unemployment in economies with high and low degrees of automation.

D Model Specification with Random Search

Section 4.5 isolates the mechanisms through which automation flattens the price Phillips curve by comparing the baseline model to alternative specifications in which rather than directed search the form of the labor market friction is due to random search, where we can specify the degree of bargaining power of workers. In this section, we detail how this change alters the equilibrium conditions of the model.

As in the baseline model, the producers that decide to operate with a labor technology have to post a vacancy in the labor market, taking into consideration the probability of filling it with one of the individuals that are actively looking for a job. However, in this case we abstract from the presence of a continuum of sub-markets, and consider that all firms post vacancies in the same market.

Let v_t be the number of vacancies being posted and N_t the measure of individuals who search for a job. The flow of matches, $x_t(v_t, s_t)$, is pinned down by the matching function

$$x_t(v_t, s_t) = \xi v_t^{\eta} s_t^{1-\eta}, \tag{D.1}$$

where η is the elasticity of the matching function with respect to vacancies, and ξ denotes the matching efficiency. Matches continue to last for one period.

Upon a match, workers and firms bargain on the wage (define the real wage by w_t) by splitting the total surplus of the match. Firms are heterogenous with respective to their labor productivity level and would have the incentive to claim they have the lowest productivity level, $\gamma_t^{\star}$, to maximize their surplus. Workers, therefore cannot identify the productivity level of the matched firm. However, workers have information on prices and the distribution of productivity levels across firms, and therefore can obtain the expected value of the matched firm's surplus, by inferring the set of firms who posted vacancies (firms whose $\gamma_j > \gamma_t^{\star}$, thus total vacancies $v_t = \Xi_{L,t} = \Xi_t \int_{\gamma_t^{\star}}^{\gamma_H} f(\gamma)\, \mathrm{d}\gamma$), and predicting the relative price $q_{P,t}$. Workers then set the expected value of the surplus of firms who participate in the labor market to be[23]

$$\begin{aligned}
\mathbb{E}_t\left[S_t\right] &= \int_{\gamma_t^\star}^{\gamma_H} \left[q_{P,t}\gamma - w_t\right] f(\gamma)d\gamma \\
\mathbb{E}_t\left[S_t\right] &= \int_{\gamma_t^\star}^{\gamma_H} \left[q_{P,t}\gamma - w_t\right] \frac{\alpha\gamma_M^\alpha\gamma^{-\alpha-1}}{1-\gamma_M^\alpha\gamma_H^{-\alpha}}d\gamma \\
\mathbb{E}_t\left[S_t\right] &= \left\{\frac{\alpha}{\alpha-1}q_{P,t}[\gamma^{\star\,1-\alpha} - \gamma_H^{1-\alpha}] - w_t[\gamma^{\star\,-\alpha} - \gamma_H^{-\alpha}]\right\}\frac{\gamma_M^\alpha}{1-\gamma_M^\alpha\gamma_H^{-\alpha}}.
\end{aligned}$$

If individuals are matched with a producer, they get the real wage w_t, and otherwise they receive no income.[24] The wage in equilibrium, as a result of the bargaining, is given by

$$\begin{aligned}
\arg\max_{w_t} &= (w_t)^\tau(\mathbb{E}_t\left[S_t\right])^{1-\tau} \\
\text{Thus} \qquad & w_t = \tau\frac{\alpha}{\alpha-1}q_{P,t}\frac{(\gamma_t^\star)^{-\alpha+1} - (\gamma_H)^{-\alpha+1}}{(\gamma_t^\star)^{-\alpha} - (\gamma_H)^{-\alpha}}
\end{aligned}$$

Where τ denotes the bargaining power of workers. If we set $\tau = \eta = 0.5$, then firms and workers have equal bargaining power and markets are efficient (Hosios condition). Low values of τ describe an economy in which firms have more bargaining power, thus wages are compressed and firm surpluses are maximized. We exploit how altering the degree of worker's bargaining power affects the role of automation as a treat that depresses wages given an unemployment change.

We can then determine the labor market tightness, and therefore the probability of filling a vacancy. They are:

$$\begin{aligned}
\theta_t &= \frac{\Xi_t\int_{\gamma_t^\star}^{\gamma_H} f(\gamma)d\gamma}{N_t} = \frac{\Xi_t\gamma_M^\alpha[(\gamma_t^\star)^{-\alpha} - (\gamma_H)^{-\alpha}]}{N_t(1-\gamma_M^\alpha\gamma_H^{-\alpha})} \\
q_t(\theta_t) &= \xi\left(\frac{\Xi_t\gamma_M^\alpha[(\gamma_t^\star)^{-\alpha} - (\gamma_H)^{-\alpha}]}{N_t(1-\gamma_M^\alpha\gamma_H^{-\alpha})}\right)^{\eta-1}
\end{aligned}$$

The value of firm j that enters the labor market is given by

$$V_j(\gamma_j) = \xi\left(\frac{\Xi_t\gamma_M^\alpha[(\gamma_t^\star)^{-\alpha} - (\gamma_H)^{-\alpha}]}{N_t(1-\gamma_M^\alpha\gamma_H^{-\alpha})}\right)^{\eta-1}\left(p_P\gamma_j - \tau\frac{\alpha}{\alpha-1}p_P\frac{(\gamma_t^\star)^{-\alpha+1} - (\gamma_H)^{-\alpha+1}}{(\gamma_t^\star)^{-\alpha} - (\gamma_H)^{-\alpha}}\right) - \kappa$$

[23] We assume the distribution of firms is $f(\gamma) = \frac{\alpha{\gamma_M}^\alpha\gamma_j^{-\alpha-1}}{1-{\gamma_M}^\alpha{\gamma_H}^{-\alpha}}$, as in the baseline model.

[24] As in the baseline model, we abstract from unemployment benefits as we assume perfect consumption insurance within households.

Finally the expected value of a firm entering in the economy at time t is

$$\int_{\gamma_M}^{\gamma_t^\star} \left(q_{P,t}\gamma_M - q_{M,t} - \kappa\right) f(\gamma)d\gamma + \int_{\gamma_t^\star}^{\gamma_H} \left[q_t(\theta_t)\left(q_{P,t}\gamma - W_t\right) - \kappa\right] f(\gamma)d\gamma = 0$$

$$\left(1 - \gamma_M^\alpha(\gamma_t^\star)^{-\alpha}\right)\left(p_{P,t}\gamma_M - q_t\right) + \dots$$
$$\dots + q_t(\theta_t)\frac{\alpha}{\alpha-1}p_{P,t}\left(\frac{\gamma_M^\alpha\left((\gamma^\star)^{-\alpha+1} - (\gamma_H)^{-\alpha+1}\right)}{(1-\gamma_M^\alpha\gamma_H^{-\alpha})}\right) - \dots$$
$$\dots - (q_t(\theta_t)W)\left(\frac{\gamma_M^\alpha}{(\gamma_t^\star)^\alpha} - \frac{\gamma_M^\alpha}{(\gamma_H)^\alpha}\right) = \kappa\left(1 - \gamma_M^\alpha\gamma_H^{-\alpha}\right)$$

D.1 Equilibrium Conditions

Using the modified equations above, the equilibrium conditions of the model version featuring random search in the labor market are the following ones:

$$U_{C,t} = \beta \mathbb{E}_t \left[\frac{R_t U_{C,t+1}}{\pi_{t+1}} \right], \tag{D.2}$$

$$Y_t = C_t + I_t + \frac{\phi}{2}(\pi_t - 1)^2 (C_t + I_t), \tag{D.3}$$

$$\begin{aligned} &(1-\psi)(C_t + I_t) + \psi q_{P,t}(C_t + I_t) - \phi(\pi_t - 1)\pi_t (C_t + I_t) + \dots \\ &\dots + \beta \mathbb{E}_t \left[\frac{U_{C,t+1}}{U_{C,t}} \phi(\pi_{t+1} - 1)\pi_{t+1}(C_{t+1} + I_{t+1}) \right] = 0, \end{aligned} \tag{D.4}$$

$$q_{M,t} \Xi_t \int_{\gamma_M}^{\gamma_t^\star} f(\gamma) d\gamma = I_t, \tag{D.5}$$

$$\gamma_M q_{P,t} - q_{M,t} = q_t(\theta_t) \left(q_{P,t} \gamma_t^\star - w_t \right), \tag{D.6}$$

$$\begin{aligned} &\int_{\gamma_M}^{\gamma_t^\star} \left(q_{P,t} \gamma_M - q_{M,t} - \kappa \right) f(\gamma) d\gamma + \dots \\ &\dots + \int_{\gamma_t^\star}^{\gamma_H} \left[q_t(\theta_t) \left(q_{P,t} \gamma - w_t \right) - \kappa \right] f(\gamma) d\gamma = 0, \end{aligned} \tag{D.7}$$

$$\Xi_t \left(\int_{\gamma_M}^{\gamma_t^\star} \gamma_M f(\gamma) d\gamma + \int_{\gamma_t^\star}^{\infty} q_t(\theta_t) \gamma f(\gamma) d\gamma \right) = Y_t, \tag{D.8}$$

$$q_t(\theta_t) = \xi \left[\frac{\Xi_t \gamma_M^\alpha \left(\gamma^{\star\, -\alpha} - \gamma_H^{-\alpha} \right)}{N_t (1 - \gamma_M^\alpha \gamma_H^{-\alpha})} \right]^{\eta - 1} \tag{D.9}$$

$$w_t = \tau \frac{\alpha}{\alpha - 1} q_{P,t} \frac{\gamma^{\star\, 1-\alpha} - \gamma_H^{1-\alpha}}{\gamma^{\star\, -\alpha} - \gamma_H^{-\alpha}} \tag{D.10}$$

$$N_t u_t = N_t - \Xi_t q_t(\theta_t) \left(\int_{\gamma_t^\star}^{\gamma_H} \gamma f(\gamma) d\gamma \right), \tag{D.11}$$

$$N_t = \frac{w_t U_{C,t}}{\lambda_H}. \tag{D.12}$$