State Dependent Okun's Law: A Selective Labor Hoarding Approach

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Abstract

In this paper I show that Okun's Law, the relationship between changes in the unemployment rate and real GDP, is state dependent: the relationship is stronger during recessions. I hypothesize that this state dependency arises from firms engaging in selective labor hoarding. If firms hoard high-skilled workers outside of recessions to economize on training costs, the Okun relationship will be relatively flat in those times. Such labor hoarding becomes untenable during recessions, which produces a nonlinear response of unemployment. I build a dynamic model of directed search with heterogeneous firms, endogenous exit, and training costs that generates the nonlinear response of unemployment to changes in real GDP.

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1 Introduction

The *Okun's law*[1], which is the negative relationship between changes in the unemployment rate and changes in real GDP, is one of the key building blocks in modern macroeconomics models. This principle constitutes a cornerstone upon which aggregate supply is constructed. This relationship plays a very important role during recessions addressing relevant public policy issues such as the magnitude of demand expansion needed to reduce unemployment by a certain amount. I find that the magnitude of this relationship diverges markedly across expansions and recessions, thus suggesting the presence of a state-dependence within Okun's Law. Although this fact is well documented (Cuaresma (2003), Silvapulle et al. (2004), Holmes & Silverstone (2006), Knotek II (2007), Owyang & Sekhposyan (2012)), the literature has not explored theoretical mechanisms driving this result.

I hypothesize that this state dependency arises from firms engaging in selective labor hoarding of some of its employees. The intuition is that firms face a trade-off when confronted with adverse productivity shocks. On one side, firms need to cut labor costs by firing workers; on the opposite, firms also want to minimize training replacement personnel once the shock vanishes. Consequently, firms might tend to purposely hoard a fraction of their labor pool during small and transitory shocks. However, this behavior might become unfeasible in the face of profound and persistent adverse shocks. This trade-off generates an inaction region for which firms do not react to changes in output and therefore the Okun's law relationship is relatively weak. However, in recessions some firms exit this inaction region precipitating an amplification of the Okun's law.

I use aggregate national and state level data for the US to show that the Okun's law is relatively steeper during recession periods compared to expansions. This empirical result has a profound implication for economic dynamics. Specifically, the real growth needed to return to the original pre-recession unemployment rate is larger than the observed fall which initially precipitated the rise in unemployment.

I use the state level analysis to unveil the primary mechanism used in the theoretical framework. Larger and persistent negative shocks will tend to push firms outside this theoretical "inaction region" in which they tend to hoard some of their workers. I show that states with more amplified fluctuations in their unemployment rates, on average, reveal a more pronounced divergence in their Okun's Law's slopes between expansions and recessions. Further, I use CPS monthly micro data to show

[1] Posed for the first time in Okun (1963).

that the unemployed pool of workers becomes relatively older, more educated and it includes workers from higher paid occupations at the troughs of recessions compared to other business cycle phases. This empirical fact also suggests that firms tend to try to hoard a fraction of their workers when facing negative but small or less persistent shocks. I argue in the model section that a plausible channel that could generate this behavior is the presence of training costs invested in their workers.

I build a dynamic model of directed search with heterogeneous firms and show that this model replicates the Okun's law state-dependence. The model has two main components that are consistent with this state-dependence. First, it allows for endogenous firm exit resulting in disproportionally higher exit rates from the least productive firms in recessions. This mechanism is present in Schaal (2017) due to the presence of fixed operating costs, however, I show that in isolation, this mechanism proves insufficient to underpin the stronger reaction of unemployment during crises that we observe in the data. Second, I incorporate training costs which incentivize firms to hoard workers, who now become more expensive to train, during adverse shocks. I show that the model is able to generate the Okun's law state dependence.

This paper contributes to the empirical literature that underscores the asymmetrical reaction of unemployment in response to shifts in real output (Cuaresma (2003), Silvapulle et al. (2004), Holmes & Silverstone (2006), Knotek II (2007), Owyang & Sekhposyan (2012)). In this paper I focus on filling the gap in regards to the theoretical framework driving this result.

I also contribute to the literature of theories of unemployment dynamics along the business cycles (Caballero & Hammour (1996), Berger et al. (2012), Chodorow-Reich & Karabarbounis (2016), Blanco & Navarro (2016), Christiano et al. (2020)). These seminal voices proffer mechanisms explaining the relatively stronger rises of unemployment rate compared to its declines. Yet, these papers do not focus on the elasticity of unemployment rate with respect to output. More recent literature have sought to address the overreaction of unemployment rate (Dupraz et al. (2019), Hazell & Taska (2020)). These papers use nominal wage downward rigidities to generate unemployment overshooting. I show that a model without these wage rigidities is able to generate this behavior of unemployment extending these results to the shape of the Okun's law.

Another strand of the literature (Burnside et al. (1993), Horning (1994), Sbordone (1996)) introduced the labor hoarding mechanism from the vantage of firms. This mechanism entails the maintenance of an inefficient quantity of labor during periods characterized by adverse shocks. Labor hoarding consists in maintaining an inefficiently amount of labor during negative shocks in order to avoid not only the usual firing costs and hiring costs once the shock vanishes but also the training costs for when the firm fills the position again in the following recovery. This paper contributes to this literature by introducing labor hoarding within a structured directed search model and I show that selective labor hoarding is key to generate the overreaction of unemployment to the state of the economy.

Nonetheless, it is plausible that firms might not hoard their workers randomly, instead they might exhibit an element of selectivity whereby lower-skilled workers are disproportionately subjected to displacement during adverse shocks, as opposed to their higher-skilled counterparts. The mechanism I propose that might generate the Okun's law state dependence is selective labor hoarding, that is, firms tend to fire proportionally more workers who have been trained less intensively and hoard proportionally more workers who have been trained more intensively. I incorporate the dimension of training costs in a dynamic directed search model. This feature capitalizes on the empirical underpinning articulated by Bassanini & Ok (2004) and Dube et al. (2010) who find that replacement costs are higher for larger firms, higher wages and more high skilled occupations. This idea comes from the fact that in non-competitive labor markets wages increase in the level of training but less abruptly than productivity so the gap between productivity and wage is higher at greater skill levels underscored by Acemoglu & Pischke (1999).

Moreover, smaller firms are more cyclically sensitive than larger and more productive one (Kim & Burnie (2002), Fort et al. (2013), Crouzet et al. (2017)). This implies that low skilled workers, which are over-represented in smaller and less productive firms (Barron & Bishop (1985), Barth et al. (1987), Brown & Medoff (1989), Abowd et al. (1999)). Consequently, these workers are more likely to lose their job in any state of the economy. Conversely, high-skilled workers find representation in larger and more productive entities, which fosters a greater likelihood of job retention in any state.

This suggested mechanism is consistent with Mueller (2017)'s findings, wherein the pool of unemployed workers becomes relatively more high skilled during recessions when compared to normal times. This reconciles with the two principal mechanisms underscored within the model. On the one hand, this finding aligns with the fact that a larger fraction of more productive firms start to shut down only at the trough phase of the business cycle. Since these firms on average employ more high skilled workers than the least productive firms, this could explain this change in the composition of the unemployment pool. On the other hand, an alternative consistent explanation would be that all firms, when confronted with a large negative shock, they exit the "inaction region" and stop being able to hoard their more high-intensively trained workers resulting in disproportionate layoff rates for this group of workers.

The paper is structured as follows: in Section 2 I present the main stylized fact that I aim to replicate in the context of the Okun's law regression. In Section 3 I present the theoretical framework – a directed labor search model replete with firm-worker heterogeneity. This conceptual framework incorporates training costs. In Section 4 I provide the model's results, unveiling the extent to which this articulated mechanism serves as an accurate descriptor of the aforementioned asymmetrical comportment inherent to the Okun's law. Finally, in Section 5 I present the paper's conclusions.

2 Data and Stylized Facts

In this section I first describe the results from aggregate data, lay out the basic Okun's law, and I present its state-dependence using OLS regressions. Second, I present Integrated Public Use Micro-data Series (IPUMS) Current Population Survey (CPS) data that I will use to present micro evidence of the proposed theoretical mechanism.

2.1 Aggregate Data: State Dependent Okun's law

I use quarter-on-quarter real GDP growth and changes in seasonally adjusted unemployment rate for the US economy since 1948:I to 2021:IV provided by the Federal Reserve Bank of St. Louis and the US Bureau of Labor Statistics. The BLS provides data on unemployment rate at a monthly frequency, so I convert it to quarterly frequency using the average of the three months comprising each quarter.

In order to objectively identify recessionary periods, diverging from the somewhat arbitrary definitions by the National Bureau of Economic Research (NBER), I use the algorithm proposed by Dupraz et al. (2019), which delineates expansionary and recessional intervals contingent upon the evolution of the unemployment rate[2]. The reason I use this algorithm is that I want to be able to compare the simulated model outcomes with the empirical observations. In Table 1 I show a comparison of the recession dates with respect to the NBER ones. It is noteworthy, as acknowledged by the authors, that this algorithm treats the double-dip recessions of the 1980s as a singular and protracted episode. Moreover, the algorithm tends to detect larger

[2]For detailed insights, refer to A.1.

recession durations compared to the NBER, with a total of 107 recession quarters instead of 56 in my full sample.

Table 1: NBER dates vs. Algorithm Dates

Order	NBER dates	Algorithm dates
1	1948q4 - 1949q4	1948q2 - 1949q4
2	1953q2 - 1954q2	1953q2 - 1954q3
3	1957q3 - 1958q2	1957q1 - 1958q2
4	1960q2 - 1961q1	1959q2 - 1961q2
5	1969q4 - 1970q4	1969q1 - 1971q3
6	1973q4 - 1975q1	1973q4 - 1975q2
7	1980q1 - 1980q3	1979q1 - 1982q4
8	1981q3 - 1982q4	-
9	1990q3 - 1991q1	1989q1 - 1992q3
10	2001q1 - 2001q4	2000q3 - 2003q2
11	2007q4 - 2009q2	2007q1 - 2009q4
12	2019q4 - 2020q2	2019q4 - 2020q3

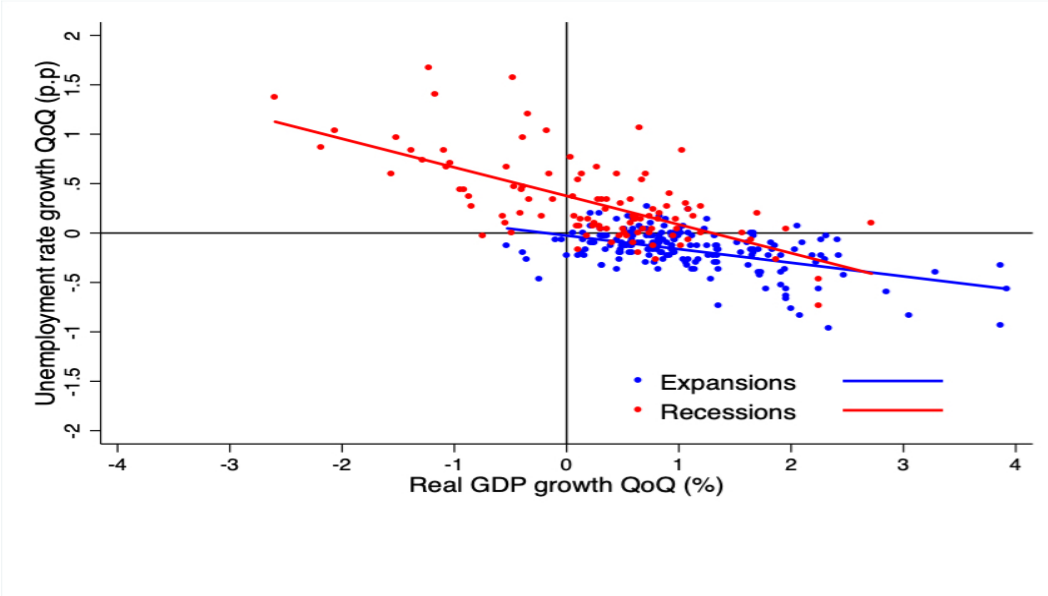
Real GDP has been growing on average at 0.78% per quarter. However, growth rates are substantially lower during recession periods, 0.20%, while expansionary phases are characterized by higher growth rates, 1.1%[3]. The average unemployment rate stands at 5.76%. However, during the recessionary cadence, this metric scales to 5.91%, while it registers a marginally diminished threshold of 5.67% throughout expansionary phases[4]. Furthermore, during recessions, the unemployment rate rises by an average of 0.35 percentage points per quarter, juxtaposed against a contraction of 0.20 percentage points per quarter within expansions. Figure 1 shows the evident state-dependence of the Okun's law relationship. Notably, this visualization excludes the most recent COVID-induced recession, as the pronounced deviation of data points from the axes could potentially obscure the overarching pattern. All regression analyses will include the entire sample period, including the most recent COVID episode.

I show the results of the Okun's law in Table 2. In column (1) I show the results of the full sample period ignoring recession and expansion differences and in column (2)

[3]It is notable to emphasize that this divergence arises due to the treatment of the double-dip recession by the algorithm, identifying them as a singular recession period. Resorting to the NBER chronology, the growth dynamics manifest as -0.44% per quarter during recessions and 1.06% per quarter during expansions.

[4]Once again, under the NBER dates, this divergence is accentuated with unemployment rates averaging 6.05% and 5.69% during recessions and expansions, respectively.

Figure 1: State dependent Okun's Law



Note: Each point in the graph represents a quarter in the sample, in red I show recession periods and in blue expansions. I also represent the OLS fitted lines for only recession periods (red line) and only expansion periods (blue line).

I add the binary controlling for recession periods (Rec). This augmented specification further includes the interaction between real output growth and the aforementioned recession indicator, as delineated within equation (1).

$$\Delta u_t = \beta_0 + \beta_1 \Delta y_t + \beta_2 \text{Rec}_t + \beta_3 \Delta y_t \times \text{Rec}_t + \epsilon_t. \tag{1}$$

The variable Δu_t embodies the quarter-on-quarter variation in the unemployment rate, while Δy_t represents the corresponding quarter-on-quarter growth rate of real GDP. On average, a 1 percentage point rise in the quarter-on-quarter growth rate of real GDP correlates with a contraction of -0.48 percentage points in the quarter-on-quarter differentials of the unemployment rate. This elasticity drops when the tumultuous influence of the COVID-19 crisis is excluded from the sample, resulting in a scaled-down magnitude of -0.28. This effect is statistically significant at the 1 percent threshold. Notably, the constant term, positioning itself at 0.37, signifies that in the absence of real GDP expansion, the unemployment rate burgeons by an average of 0.37 percentage points each quarter.

In column (2) I include the binary recession and its corresponding interaction with the quarter-on-quarter real GDP growth rates. When real output does not grow

($\Delta y_t = 0$) the unemployment rate barely changes during expansionary periods. This stands in stark contrast to the recessionary landscape where the unemployment rate experiences a significant rise, up by an average of 0.51 percentage points each quarter ($\hat{\beta}_2 = 0.51$) when there is no real growth in GDP. The Okun's law main slope also differs substantially during economic recessions. In recessions, a 1 p.p. decline in the real GDP growth rate translates to a substantial rise of 0.61 percentage points in the unemployment rate ($\hat{\beta}_1 + \hat{\beta}_3 = -0.14 - 0.47 = -0.61$). In contrast, the increment during periods of economic expansion merely hovers at an average of 0.14. Therefore, during recessions the Okun's law relationship becomes steeper. Another insight within the regression analysis can be found in the variation in the R-squared coefficient. Introducing the binary variable *Recession* and its interaction component rises the R-squared from 0.60 to 0.72. Columns (3) and (4) provide an alternate perspective, excluding the influence of the most recent pandemic episode. The recessionary binary coefficient becomes now smaller ($\hat{\beta}_2 = 0.4$), while the slope transformation becomes now only twice steeper in recessions ($\hat{\beta}_3 = -0.15$). Importantly, all coefficients perpetually retain statistical significance at the 1 percent level.

The ramifications of Okun's law state dependence are quite relevant policy-wise. Within the contours of recessional dynamics, it becomes patently evident that the labor market acquires an augmented degree of responsiveness to changes in GDP compared to expansion periods. In effect, the dynamics signify that a linear and invariable Okun's law would have underpinned notably subdued unemployment rates during the majority of the recessions identified by the algorithm spanning the temporal spectrum from 1948 onwards. I present this fact in Figure 2, which compares the actual observed unemployment rate with the predicted by a basic Okun's law rooted in the coefficients from column (1), and the projections emerging from the coefficients of column (3), excluding the COVID-19 crisis. A discernible pattern emerges, underscored by the recurrent propensity of actual unemployment rates to outstrip the projections posited by a constant Okun's law, grounded in the observed shifts in real output. During the 2009 crisis, which witnessed an average unemployment rate of 6.57%, eclipsing its anticipated counterpart by nearly 1 percentage point within the framework of a constant Okun's law. Notably, this discrepancy expands to almost 3 percentage points when I exclude the COVID-19 period for the prediction. A parallel iteration of this analytical exercise, grounded in the NBER dating, is embodied within Figure A.1, corroborating the overarching observation that actual unemployment rates consistently surpass those predicted through a constant invariable Okun's law throughout all 12 recessional episodes.

Table 2: Okun's law: expansions vs. recessions

	Full sample		No COVID-19	
Variables	(1)	(2)	(3)	(4)
	Δu_t	Δu_t	Δu_t	Δu_t
Δy_t	-0.475***	-0.139***	-0.277***	-0.138***
	(0.115)	(0.022)	(0.023)	(0.022)
Recession		0.511***		0.401***
		(0.077)		(0.041)
Recession x Δy_t		-0.465***		-0.152***
		(0.136)		
Constant	0.369***	-0.043	0.216***	-0.026
	(0.105)	(0.026)	(0.027)	(0.024)
Observations	295	295	287	287
R-squared	0.602	0.719	0.460	0.608

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: Column (1) represents the simple Okun's law regression with changes in seasonal unemployment rate quarter on quarter as the dependent variable and quarter on quarter changes in real GDP as the independent variable. In column (2) I add the binary Recession corresponding to the dates that the algorithm finds, being equal to 0 during expansions and 1 during recessions. The interaction term is the multiplication of the binary Recession with the change in real GDP quarter on quarter. The time range is 1948:I - 2021:IV. Columns (3) and (4) are analogous to (1) and (2) but restricting the sample to 2019:IV, so excluding the COVID-19 crisis.

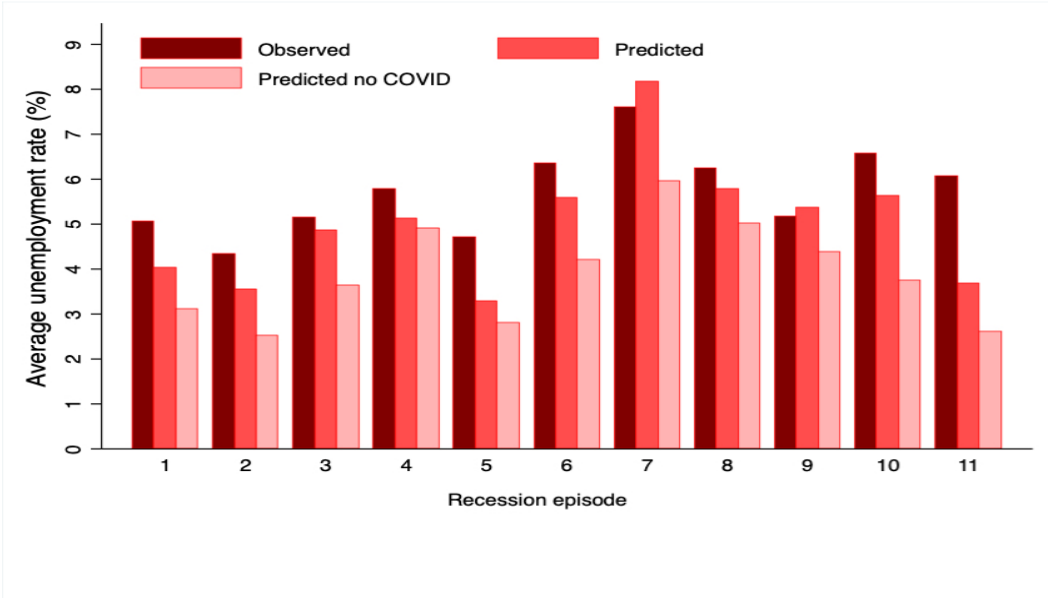
2.2 State-level analysis

I run the same analysis at the state level using quarterly data from 2005 to 2022. I use data from the Bureau of Economic Analysis and collapse the monthly data from unemployment to a quarterly frequency to match it with the real GDP. In Table 3 I present results for the Okun's law in a yearly panel data that correspond to the following regression:

$$\Delta u_{st} = \alpha_0 + \alpha_1 \Delta y_{st} + \alpha_2 \text{Rec}_{st} + \alpha_3 \Delta y_{st} \times \text{Rec}_{st} + \mu_s + \epsilon_{st}. \tag{2}$$

The subscript s is used to represent distinct states, and μ_s is the state fixed effect. As with the national analysis, the incorporation of the "Recession" term rises the R-squared coefficient, elevating it from 0.51 to 0.68. It is important to notice that now recessions are state-specific. Again, the interaction of term of the recession binary and real growth experiences a notable rise during recessions. Further, I use the algorithm to identify state-specific recession periods across the cohort of 51 states (comprising

Figure 2: Implication of the state dependent Okun's Law



Note: Each number in the x-axis represents a recession identified by the algorithm. The first corresponds to the 1948:II - 1949:IV and the last one to the 2019:IV - 2020:III one.

50 states plus the District of Columbia). This determination is obtained using the respective trajectories of unemployment rates that unfold across each state. In Figure 3 I show the quantity of states in recession in each period of time. We can see two clear spikes that coincide with the occurrence of the two recessions manifesting within this temporal scope.

The use of state-level data allows me to introduce an outline of the main theoretical mechanism. Each firm will have an inaction region as a function of aggregate negative shocks (z_t). When the shocks are small enough, up to $\underline{z}$ firms might not fire any worker, however there will be a region between $\underline{z}$ and $\bar{z}$ in which firms will only fire their less expensive to train workers. When shocks are large and persistent enough firms will eventually exit the inaction region and start firing high skilled workers as well. However, from Figure 4 one could argue that our mechanism does not necessarily imply a relatively steepening of the Okun's law in recessions. Consider a hypothetical scenario of a very rich country. During expansions most of its firms are located far to the left from the inaction region and when a recession hits they enter it resulting in a flatter relationship in recessions. Another possibility would be that most firms are already in the inaction region but closer to $\underline{z}$ such that in a recession they do not abandon it. Contrary, if a country already has most of the firms closer to $\bar{z}$ in normal

Table 3: Panel data with state fixed effects

	Full sample		No COVID-19	
Variables	(1)	(2)	(3)	(4)
	Δu_t	Δu_t	Δu_t	Δu_t
Δy_t	-0.473***	-0.066**	-0.083***	-0.013***
	(0.038)	(0.032)	(0.014)	(0.003)
Recession		0.665***		0.488***
		(0.027)		(0.019)
Recession x Δy_t		-0.543***		-0.114***
		(0.031)		(0.022)
Constant	0.153***	-0.180***	0.005	-0.149***
	(0.014)	(0.015)	(0.005)	(0.005)
Observations	3,672	3,672	3,009	3,009
R-squared	0.513	0.682	0.079	0.414

Clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

times, when a recession hits the economy they will very likely exit it resulting in a steeper Okun's law relationship.

Employing the framework in equation (1), I run the Okun's law regression for all states and focus on $\hat{\beta}_3$. This coefficient resonates with the interaction term, quantifying the extent of slope deviation within the Okun's law framework during recessions vis-à-vis expansions. I expect that the states showing more pronounced fluctuations in unemployment rates, so more likely to cross the $\bar{z}$ threshold, will have more pronounced negative coefficients during recessions, so more negative β_3. In contrast, states with lesser variance in unemployment rates, so less likely to surpass the $\bar{z}$ threshold amid recessionary headwinds, I expect them to experience softer β_3 coefficients.

In Figure 5 I show the relationship between the standard deviation of state unemployment rate and the interaction term $\hat{\beta}_3$. The discernible trend materializes as states characterized by larger unemployment rate oscillations correspondingly exhibit steeper interaction terms (β_3 of equation (1)). This empirical fact is statistically significant, deviating significantly from the null hypothesis at the robust 1.2 percent level. An outlier of this pattern is the state of Nevada with a markedly elevated standard deviation within its unemployment rate. Aligning within this trajectory, states such as Rhode Island, Michigan, California, and Hawaii with similarly elevated unemployment rate oscillations experience higher relative steepness during recessions

Figure 3: Number of US states in recession according to the algorithm

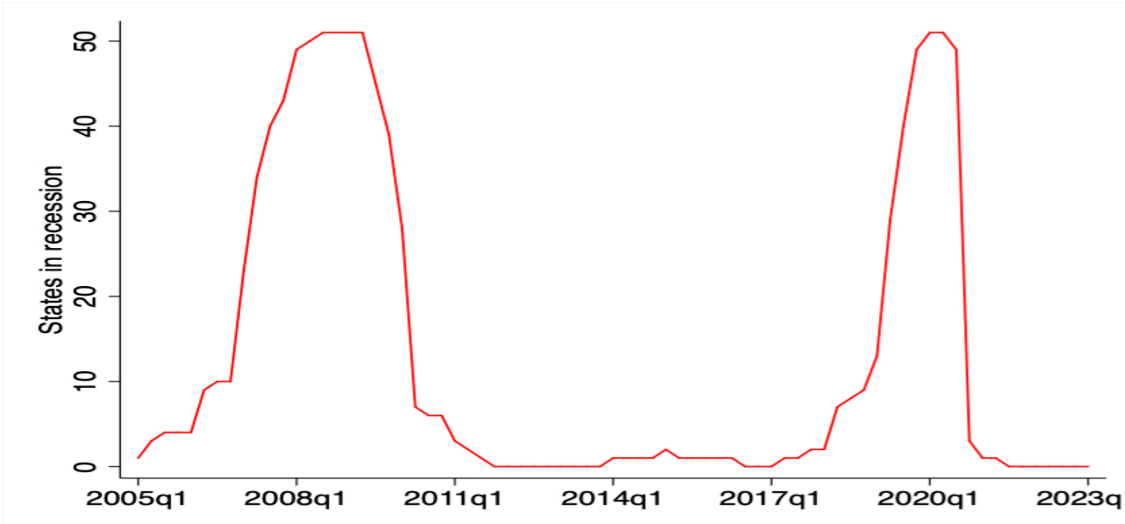
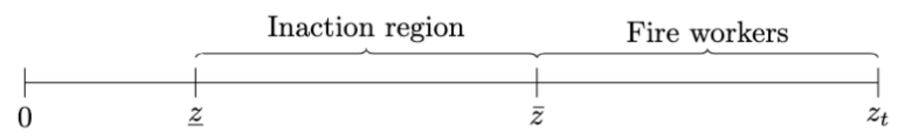


Figure 4: Sketch of the labor hoarding mechanism

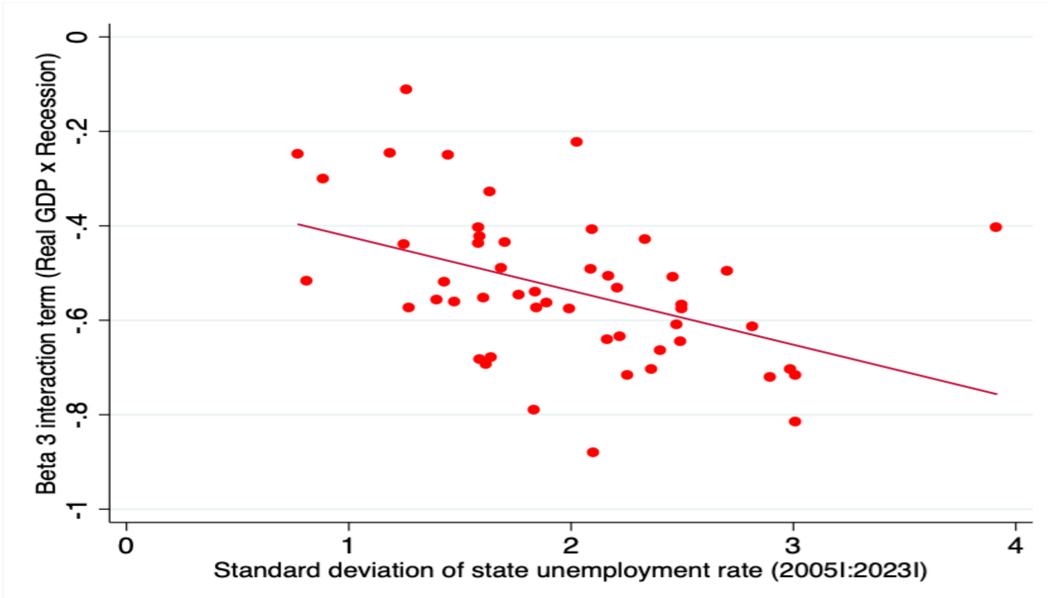


A higher z represents a larger negative shock that a firm faces. $\underline{z}$ is the threshold for which firms start firing low-intensively trained workers, $\bar{z}$ represents the threshold for which firms start firing also high-intensively trained workers.

compared to expansions. By contrast, the lowest oscillations are found in Nebraska, North Dakota, and South Dakota. I explore alternative specifications in Figure A.2, using the average state unemployment rates on the horizontal axis, and in Figure A.3 using the maximum unemployment rate within the same axis. In the latter specification, the relationship is only statistically significant at a more modest 14 percent level.

I run some robustness analysis and I show them in Table 4. Within this context, I run regression (1) but using quarter-on-quarter deviations from the Non-Accelerating Inflation Rate of Unemployment (NAIRU) as the dependent variable. Instead of quarter-on-quarter percentage changes in real GDP, the independent variable I use is the cyclical component of the logarithm of real GDP. In Table A1 I run the same robustness check but using the same independent variable as in Table 2, so the quarter-on-quarter percentage changes in real GDP. The Okun's law state dependence is

Figure 5: Okun's law state dependence by state



robust to these various specifications both at the aggregate and the state levels.

Finally, I also present the Okun's law coefficients when using the NBER dates in Table A2. The results remain unchanged. Within this framework, Column (1) mirrors the counterpart of Column (2) in Table 2, while Column (2) mirrors the analytical exploration akin to Column (2) within Table 4.

Notably, the keystone finding—the Okun's law state dependence—remains present in all specifications. During recessions, unemployment tends to increase faster even in the face of unvarying real GDP conditions (reflected in the elevated constant term). Moreover, the responsiveness of unemployment to any change in real output also escalates notably in recessions compared to expansions.

2.3 Micro data

Within this section, I present the micro-level data that will be useful to show some evidence of the mechanism substantiating the theoretical model. I use data from the Integrated Public Use Micro-data Series (IPUMS) Current Population Survey (CPS). Particularly, I use monthly data spanning from January 1976 to December 2022. In Table 5 I display summary statistics intrinsic to this dataset. I only keep individuals aged between 16 and 60 years old.

I show a strategic proclivity of firms to selectively retain a subset of their employees during expansion periods, juxtaposed against elevated layoff rates in the peaks of

Table 4: Okun's law robustness

Variables	(1) $\Delta \hat{u}_t$	(2) $\Delta \hat{u}_t$
$\Delta \hat{y}_t$	-17.436**	3.094*
	(8.965)	(1.875)
Recession		0.434***
		(0.058)
Recession x $\Delta \hat{y}_t$		-27.818***
		(12.375)
Constant	-0.002	-0.201***
	(0.037)	(0.021)
Observations	291	291
R-squared	0.167	0.344

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: I am running the same regression than the one shown in Table 2 but using quarter on quarter changes in deviations from the Non-Accelerating-Inflation-Rate-Unemployment (NAIRU) and the cyclical component of the logarithm of real GDP.

economic recessions. To this end, I collapse my data at a monthly frequency weighting by *wtfinl* as suggested by the CPS IPUMS. This serves me to analyze some key demographic trends regarding the business cycle.

Again, I use the unemployment rate dynamics to identify recessionary troughs. In order to have more observations as troughs, I extend my temporal lens to include months prior and subsequent to these troughs, within a realm confined to variances below the 0.5 percentage point threshold vis-à-vis the unemployment rate. I run the following regression:

$$y_t = \beta_0 + \beta_1 \text{Trough}_t + \epsilon_t, \tag{3}$$

where y_t are distinct demographic attributes characterizing the cohort of unemployed individuals. These attributes includes dimensions such as the average age, the aggregate proportion of individuals possessing some college education, as well as those with a college degree, alongside the current occupational spectrum. Sine all these demographic characteristics present a trend since 1976 I apply a HP filter to all these y_t variables when running the main regressions. This evolution is particularly manifest in the significant rise of the fraction of college degree holders, from 13.7% in 1976 to the current 34.8%, while the cohort with at least some college education

Table 5: CPS data description

	Mean	Std. Dev.
Age	36.95	12.73
High school or less (%)	52.18	
Some college education but no 4-y college degree (%)	24.46	
College degree or more (%)	23.36	
Employed (%)	71.99	
Unemployed (%)	4.75	
Not in the labor force (%)	23.26	
Appearances	6.23	2.15
Total observations	45,789,602	

has doubled from 30% to 60% within the span of the preceding 46 years. Further, we also see an important shift in the occupational landscape. In quantifiable terms, I establish an ordinal ranking among the 79 distinct occupations (military occupations are excluded), with the cardinal ordering benchmarked against average earnings per occupation. The occupation with the lowest average earnings would have a value of 1, corresponding to "Private Household Occupations" and highest paid one "Lawyers and Judges" would have a value of 79.

In Table 6 I show the outcomes of these regressions. In all cases, trough times are correlated with higher average ages, higher proportions of people with some college and college degrees and also workers from higher paid occupations within the unemployed pool of workers. On average, during trough months, so during months where unemployment rate peaks, the average age of the pool of unemployed workers is significantly older, its cyclical component increases by 0.48 on average, that is $\frac{3}{4}$ of its standard deviation. The cyclical component of the fraction of people with some college education but no degree also increases during trough months, by 0.01 which is a 0.9 standard deviation rise. The rise observed for the fraction of people with a college degree is more modest, only a 0.4 of a standard deviation increase. Finally, trough times are correlated with a rise in 1.2 standard deviations of the cyclical component of the occupation order of the unemployed pool, so workers from relatively better paid occupations lose their jobs at the trough of the business cycle. In Table A3 I show the same regressions but instead of regressing the cyclical component of each variable I just include year fixed effects, the results are very similar. The findings are consistent with Mueller (2017), unemployed people become relatively more educated and they belong to higher paid occupations during recession troughs compared to expansion periods.

Further validating the consistency of these findings, I show in Table A3 the same regressions but instead of regressing the cyclical component of each variable I just include year fixed effects, the results are very similar.

Table 6: Unemployed pool demographics during trough times

Variables	Cyclical Component of			
	Age	Some college	College degree	Highly paid Occupation
Trough	0.475***	0.011***	0.005**	0.951***
	(0.085)	(0.002)	(0.002)	(0.102)
β_1 / Std. Dev.	0.74	0.88	0.39	1.20
Observations	564	564	564	564
R-squared	0.046	0.069	0.014	0.122

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

This finding suggests that there is a fraction of workers who appear to retain their employment across a substantial range of the business cycle, except for the worst moments. This phenomenon could be rationalized by a "selective labor hoarding" behavior signifying the strategic inclination of firms to purposely retain a portion of their employees amidst the throes of a negative shock. However, when confronted by a sizable and enduring shock, firms might be forced to layoff these reserved workers or, in some instances, by exiting the market. This behavior may potentially explain the particular relationship between output and unemployment and its evident state-dependence. In the theoretical model I will explore in more detail this behavior, by introducing training costs in a directed search model. In essence, workers who have undergone training would be endowed with greater job security, thereby encouraging firms to preserve their positions in the face of adverse shocks, effectively fostering the phenomenon of selective labor hoarding.

3 Model

In this section I present my model that replicates the Okun's Law's dependence on the state of the economy. The model draws its foundations from Schaal (2017), a dynamic framework centered on directed search dynamics, with heterogeneous firms that function under returns to scale, stochastic aggregate productivity, endogenous separations, and on-the-job search. I will show that the integration of training costs can result in a state-dependent Okun's Law.

3.1 Main idea

In this subsection I want to explain intuitively the main theoretical mechanism. The Okun's Law postulates the inverse correlation between changes in unemployment and changes in real GDP. For illustration purposes imagine that there are two distinct labor markets operating in isolation: one catering to low-intensively trained labor and the other to high-intensively trained labor. Under such a perspective, the Okun's Law can be reformulated as follows:

$$\frac{\Delta u}{\Delta y} = \frac{\Delta u_l}{\Delta y} + \frac{\Delta u_h}{\Delta y}, \tag{4}$$

where Δu_l (Δu_h) represents the changes in the unemployment rate for low (high) intensively trained workers. That is, the slope of the Okun's Law can be decomposed between the corresponding Okun's Law for both low and high intensively trained workers. We can also assume that high-intensively trained workers are also more productive on average. The incurrence of training costs for the high type of workers introduces a mitigating factor, yielding a relatively lower responsiveness of the unemployment rate to fluctuations in GDP during periods of economic stability for this subset. This phenomenon can be identified as "selective labor hoarding", wherein firms are more likely to retain the high type of workers while cyclically engaging in a churn process for the low type ones. In the limit, this implies that the Okun's Law is mostly driven by the dynamics of the unemployment rate for the low type of workers during expansion times. Nevertheless, firms exit or start firing high skill workers during recessions, which implies that the second term of the decomposition of the Okun's Law starts increasing, which in turn makes the relationship between changes in unemployment and real GDP stronger. This is the core idea that generates a state-dependent Okun's Law.

3.2 Environment

3.2.1 Population and technology

Time is discrete. The economy is comprised by workers and firms. Both workers and firms are risk neutral in their behavior and discount the future at a common rate β. The overall measure of workers is determined exogenously, denoted as L for each time period. Workers have some associated training costs ι. Notably, the workers have an infinite time horizon.

Firms, on the other hand, exhibit endogenous dynamics, determined by the free entry condition. They collectively produce a homogeneous good. The aggregate state of the economy is denoted as $s \in \mathbb{S}$, following a Markov chain $\pi_s(s'|s)$ that governs its evolution. The aggregate productivity level is expressed as $y(s)$. Firms, while sharing a common technology, exhibit individual variations in their idiosyncratic productivity levels denoted as $z \in \mathbb{Z}$. These idiosyncratic productivity levels are also governed by a Markov chain, $\pi_z(z'|z, s)$. The production technology for a firm, employing n workers is defined as:

$$Y(s, z, n) = \exp(y(s) + z) F(n), \tag{5}$$

where $F(\cdot)$ is strictly increasing in n and it follows Inada conditions. Upon entry, firms pay sunk entry cost k_e. To generate endogenous exit, I also assume fixed operating costs k_f.

3.2.2 Labor market

Both firms and workers engage in directed search. Firms post contracts in each submarket market to attract workers. Workers visit submarkets, evaluate posted contracts posted and decide whether to accept the terms of a contract or not. Utility is transferable between firms and workers

Firms offer contracts specifying the expected lifetime utility x transferred to workers. Firms post vacancies in each submarket and compete with other firms in that market, so there is a continuum of submarkets $x \in [\underline{x}, \overline{x}]$, where $\underline{x} \geq \frac{b}{1-\beta}$, which is the present value from being unemployed, and $\overline{x} \leq \exp(\overline{y} + \overline{z})F(\overline{n})$, which is the maximum entire firm production. The upper bars reflect that maximum values these variables can take when simulating the model Firms pay a cost c for each vacancy they post. More importantly, firms also incur in training costs ι for each newly-hired workers.

In each submarket x, firms and workers match according to a matching function with constant returns to scale. Each submarket x exhibits market tightness $\theta(s, x)$, unemployed workers find jobs with probability $p(\theta)$, and firms fill vacancies with probability $q(\theta) = \frac{p(\theta)}{\theta}$. I impose standard restrictions on the functional form of the matching function such that $p' > 0$, $q' < 0$, $p(0) = 0$, and $q(0) = 1$. There is on-the-job search, so there is a relative efficiency λ of employed workers finding a job relative to the unemployed workers.

3.2.3 Contracting and Timing

Firms post contracts that are complete, state-contingent, and of full commitment. A contract specifies a wage w, a layoff probability τ, the submarket where the worker searches while employed x, and an exit dummy d. Moreover, the contract is forward-looking, so it specifies these variables at present time t and future periods, so

$$\omega_t = \{w_{t+j}, \tau_{t+j}, x_{t+j}, d_{t+j}\}_{j=0}^{\infty} \tag{6}$$

Each period has the following timing. At the beginning of the period t, workers and firms realize the aggregate state of the economy s and potential entrants decide to entry and pay the entry cost k^e or remain outside the market. Then, incumbents and entrants realize their idiosyncratic state z and decide to stay or exit the market ($d = 1$ means exit). Firms that stay in the market decide their firing probabilities τ. Firms then choose how many new workers to hire n. Finally, firms produce, pay wages to their employees and operating costs c^f.

3.2.4 Workers

The value function for an unemployed worker is:

$$\begin{aligned} U(s) = \max_{x^u(s')} \; & b + \beta \mathbb{E} \{ p(\theta(s', x^u(s'))) x^u(s') \\ & + (1 - p(\theta(s', x^u(s')))) U(s'), \end{aligned} \tag{7}$$

where b are benefits of leisure. An unemployed worker selects the submarket x^u he wants to work in. This implies a trade-off. Choosing a higher x^u increases their utility, but it also reduces the probability of them matching $p(\cdot)$. If there is no matching, the unemployed worker receives its continuation value.

The value function of a worker working for a firm with productivity z is:

$$\begin{aligned} W(s,z) = & w + \beta \mathbb{E} \{ (d + (1-d)\tau) U_k(s') \\ & + (1-d)(1-\tau)(\lambda p(\theta(s', x')) x + (1 - \lambda p(\theta(s', x'))) W(s', z')) \end{aligned} \tag{8}$$

While employed, worker receives wage w. In the next period, different scenarios can happen. First, the worker could enter unemployment either due to firm exit or because he was laid-off. All this happens with probability $d + (1 - d)\tau$. In case this happens, the worker obtains the value $U(s')$. Second, the worker could continue to stay employed by the same firm with probability $(1 - d)(1 - \tau)$. In case this happens, the worker can either change jobs and work in a new submarket so it receives benefit x with probability $\lambda p(\theta(s', x'))$, or it decides not to change jobs and it remains with the company and receives the continuation value $W(s', z')$ with probability $1 - \lambda p(\theta(s', x'))$.

3.2.5 Firms

Consider the maximization problem of a firm with productivity z that currently hires n workers. Each worker is identified by an index $j \in [0, n]$. Firm's value function is then:

$$\begin{aligned} J(s, z, n) = \max_{n_i, x_i, \{\omega(j)\}_{j\in[0,n]}} \quad & \exp(y(s) + z) F(n) \\ & - k_f - \int_0^n w(j)\, dj + \beta \mathbb{E}\{(1 - d) \\ & \left(-n_i \left(\frac{c}{q(\theta(s', x_i))} + \iota\right) + J(s', z', n')\right) \end{aligned} \tag{9}$$

$$\begin{aligned} \text{s.t.} \qquad n'(s', z') = & \int_0^n (1 - \tau(s', z'; j))(1 - \lambda p(\theta(s', x(s', z'; j))))\, dj \\ & + n_i(s', z'), \quad \forall s', z'. \end{aligned}$$

In the current period, a firm receives revenue from production, it pays wages and operating costs. In the next period, different scenarios can happen. If the firm exits, it does not receive anything, so with probability $1 - d$ the firm continues operating. If it does, then the firm chooses how many low and high skill workers to hire. By doing this, the firm pays vacancy and training costs. Finally, firms receive their continuation values. The firm maximizes its value function subject to the dynamics of its employment history.

3.2.6 Joint surplus maximization

The joint surplus maximization problem can be expressed as:

$$
\begin{aligned}
V^A(s,z,n) = \max_{n_i,x_i,\tau,x,d} \quad & \exp(y(s)+z)F(n) - k_f + \beta\mathbb{E}\Big\{ndU(s') \\
& + (1-d)\Big[U(s')\int_0^n \tau dj + \int_0^n (1-\tau)\lambda p(\theta(s',x))xdj \\
& - \left(\frac{c}{q(\theta(s',x_i))} + \iota + x_i\right)n_i + V^A(s',z',n')\Big]\Big\}
\end{aligned} \tag{10}
$$

$$
\text{s.t.} \qquad n' = \int_0^n (1-\tau)\left(1-\lambda p\left(\theta\left(s',z',j\right)\right)\right)dj + n_i\left(s',z'\right), \quad \forall
$$

3.2.7 Free entry

Firms enter to the point where expected profits equal entry cost k_e, so free entry implies

$$
k_e = \sum_z J_e(s,z)\, g_z(z), \quad \forall s \tag{11}
$$

where $J_e(s,z)$ is the value of a potential entrant entering the market. Firms do not know what idiosyncratic shock z they will receive, so I integrate that out. Finally, this free entry condition should hold for every state of nature s. The value of a new entrant is:

$$
\begin{aligned}
J_e(s,z) = (1-d_e(s,z))\,[&\exp(y(s)+z)\,F(n_e) - k_f \\
&- \left(\frac{c}{q(\theta(s,x_e))} + \iota + x_e\right) + \beta\mathbb{E}\left\{V^A(s',z')\right\}
\end{aligned} \tag{12}
$$

Several noteworthy observations emerge from the free entry condition. To begin with, it becomes evident that entrants only obtain value when they do not exit, accounting for the presence of $1-d_e(s,z)$ in this context. Notably, variables marked with an e subscript signify their association with entrants. In the scenario where the entrant does not exit, the subsequent period it receives in expectation the value of continuing operating as an incumbent now $V^A(\cdot)$.

Next, I define the minimal hiring cost for each labor market:

$$\kappa\left(s\right)=\min_{\underline{x}\leq x\leq\overline{x}}\left\{\frac{c}{q\left(\theta\left(s,x\right)\right)}+\iota+x\right\}, \tag{13}$$

where notice that $\kappa\left(s\right)$ does not depend on the firm. Only the submarkets in each labor market that minimize this hiring cost actually open, so we have the slackness condition:

$$\theta\left(s,x\right)\left[\frac{c}{q\left(\theta\left(s,x\right)\right)}+\iota+x-\kappa\left(s\right)\right]=0,\quad\forall x,s. \tag{14}$$

With this I can then express the market tightness condition for each labor market

$$\theta\left(s,x\right)=\begin{cases}q^{-1}\left(\frac{c}{\kappa(s)-x-\iota}\right) & ,x\leq\kappa\left(s\right)-c\\ 0 & ,x>\kappa\left(s\right)-c\end{cases} \tag{15}$$

3.2.8 Unemployment and firm distribution dynamics

Let u be the aggregate unemployment rate of the economy. I can also have the employment distribution across firms as $g\left(z,n\right)$. I can then write each unemployment rate as:

$$\begin{aligned}u'=&\big(1-p(\theta(s',x_u(s')))\big)u\\&+\sum_{z,z',n}n[d(s',z';n)+(1-d(s',z';n))\tau(s',z';n)]\pi_z(z'|z,s)g(z,n).\end{aligned} \tag{16}$$

3.3 Calibration

I used the parametrization introduced by Schaal (2017). I will show results for a two segmented labor markets, one with training costs and another without. In Table 7 I show the parameters and fuctional forms used in the model.

4 Results

To begin, I will present outcomes only for the case with no training costs ($\iota=0$), and the other incorporating such costs ($\iota>0$).

Following an exogenous shock to productivity, I show the impulse responses exhibited by pivotal variables within the model. Figures 6 and 7 show the impulse

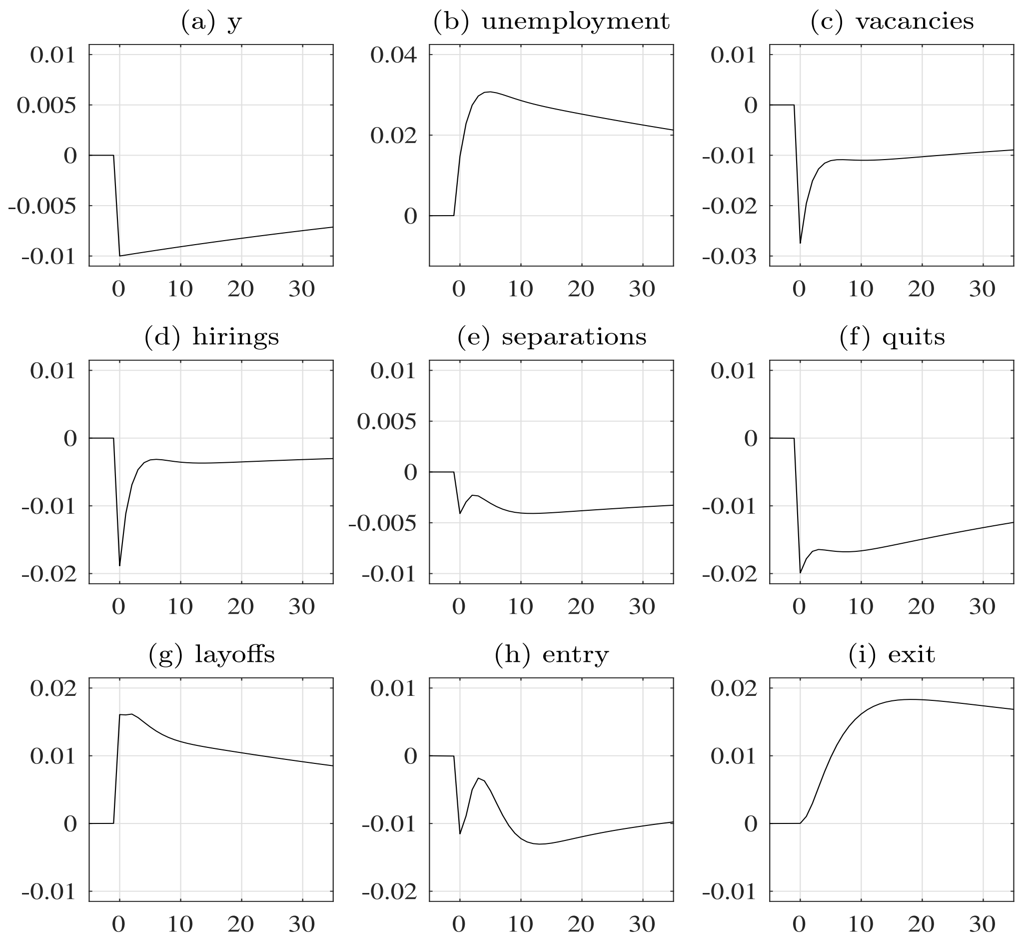
Table 7: Calibrated parameters and functional forms following Schaal (2017)

Parameter	Value	Description
β	0.996	Monthly discount factor
$F(n)$	n^{α}	Production function
$p(\theta)$	$\theta(1+\theta^{\gamma})^{-\frac{1}{\gamma}}$	Matching function
y_t	$\rho_y y_{t-1} + \sigma_y(1-\rho_y^2)^{\frac{1}{2}}\epsilon_{y,t}$	Aggregate productivity
z_t	$\rho_z z_{t-1} + \nu_z(1-\rho_z^2)^{\frac{1}{2}}\epsilon_{z,t}$	Idiosyncratic productivity
α	0.85	Decreasing returns to scale
ρ_z	0.983	Autocorrelation of idiosyncratic productivity
ρ_y	0.99	Autocorrelation of aggregate productivity
σ_y	0.042	Standard deviation of aggregate productivity
σ_z	0.132	Standard deviation of idiosyncratic productivity
b	1.403	Home production
c	1.789	Vacancy cost
λ	0.366	Relative search efficiency of employees
γ	1.599	Matching function parameter
k_e	14.21	Entry cost
k_f	1.956	Operating cost

responses triggered by negative and positive shocks in aggregate productivity respectively. There are no training costs. The unemployment rate showcases a more pronounced reaction following a positive 1% surge in productivity in comparison to a negative 1% downturn. This outcome appears contrary to the predominant empirical observation of the state-dependent Okun's law. Specifically, a 1% decline in output translates to an initial increase in the unemployment rate by 3 percentage points, whereas a 1% rise in output corresponds to an initial drop in the unemployment rate by 6 percentage points. Analogously, a parallel phenomenon is discernible with respect to layoffs—their responsiveness is more pronounced subsequent to a positive output shock as opposed to a negative one.

Incorporating training costs into the same model ($\iota = 1$) does show a state-dependent Okun's Law. In Figures 8 and 9 I show the same impulse responses but including training costs in the model. Following a negative shock, the response of the unemployment rate is more pronounced in comparison to that ensuing a positive

Figure 6: Impulse response after a negative productivity shock without training costs.

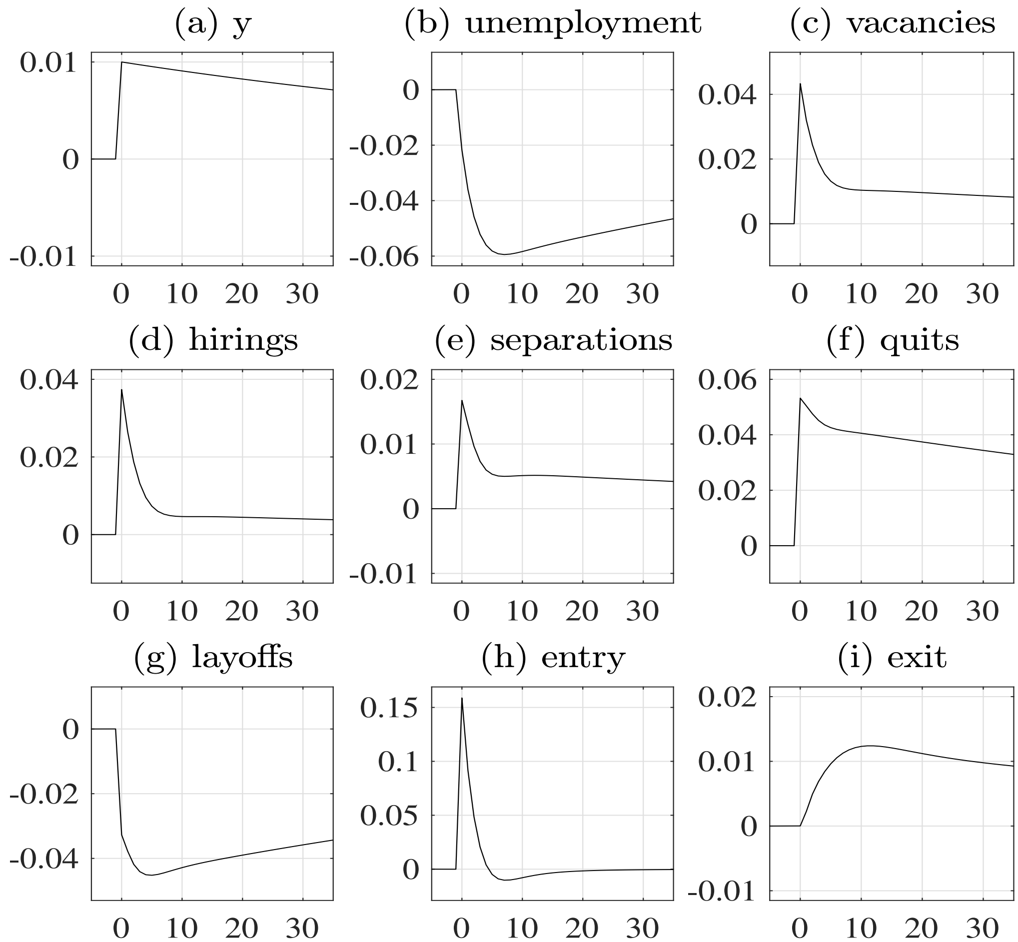


shock. For a 1 p.p. reduction in real GDP unemployment increases by 5 p.p. whereas a 1 p.p. rise in real GDP is followed by a more modest reduction in unemployment of only 3 p.p.. This trend diverges from the scenario with no training costs. Similarly, a parallel pattern is discernible in relation to layoffs, which showcase a more pronounced rise subsequent to a negative shock as opposed to the corresponding decrease prompted by a positive shock.

Interestingly, the difference in terms of the unemployment reaction is not due to different firm exit rates since they do not differ substantially between the two models. Nevertheless, the main difference comes in firms' layoffs as the main hypothesis suggested.

Lastly, in Figures 10 and 11 I repeat the same impulse response exercises but with

Figure 7: Impulse response after a positive productivity shock without training costs.

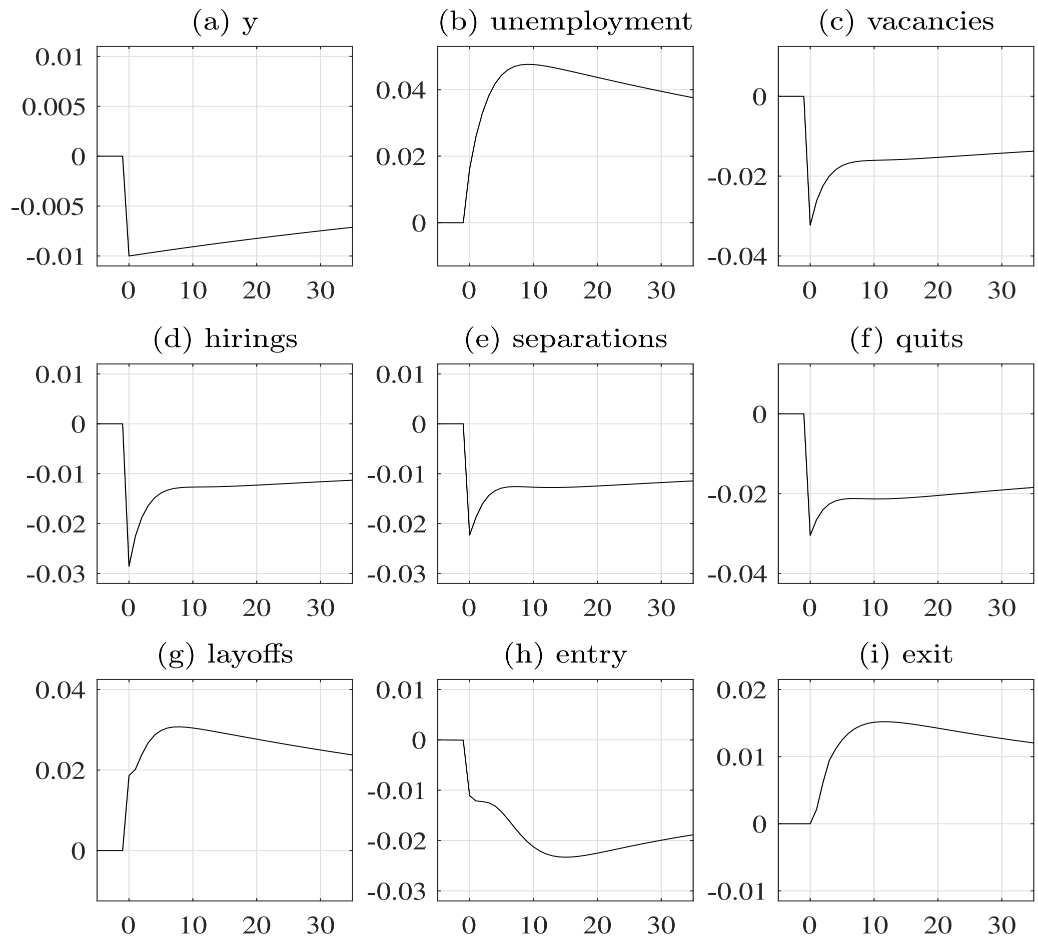


a smaller productivity shock, only a .1 p.p. change instead of a 1 p.p. change as before. In this case, the unemployment reaction is almost identical in the negative shock scenario versus the positive shock scenario. Therefore, in order to observe the asymmetric reaction of unemployment rate we need the shock to be large enough, so a recession, in order for firms to exit the inaction region.

5 Conclusions

In this paper I propose a theoretical mechanism in order to explain the apparent state-dependence in the Okun's law relationship, for which I provide robust macro

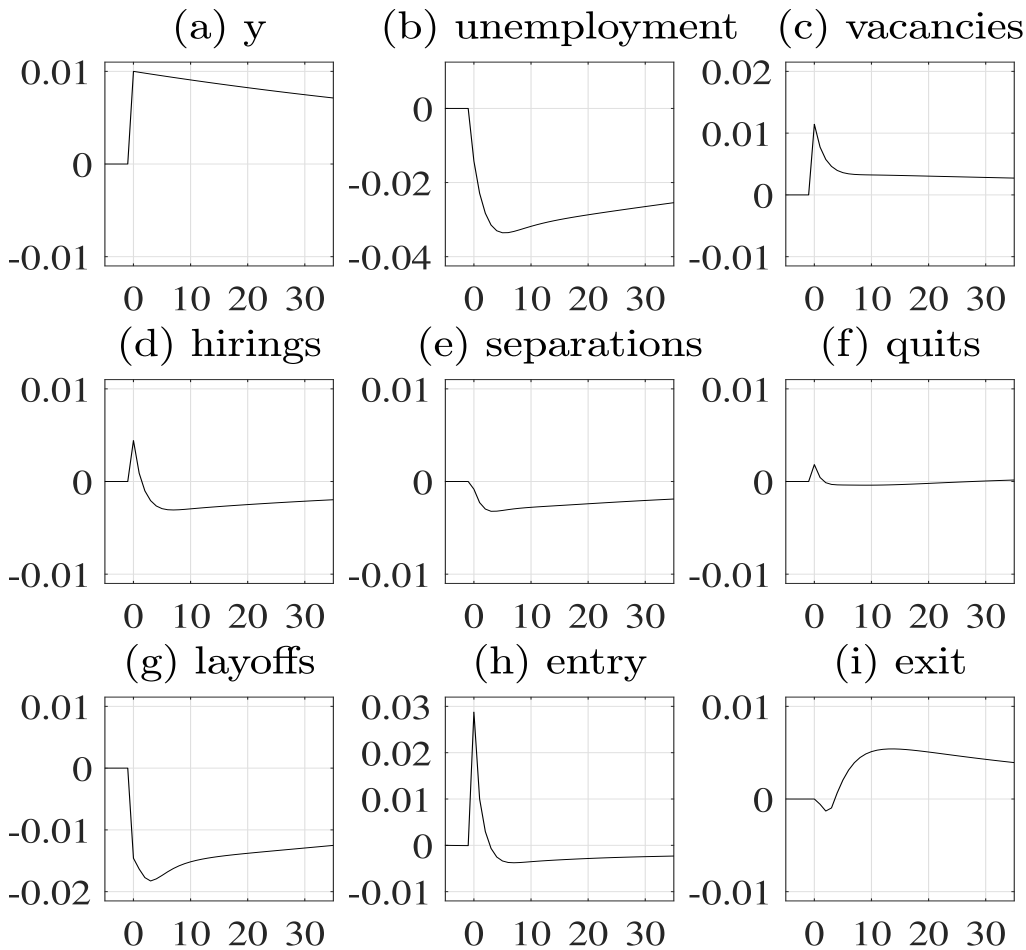
Figure 8: Impulse response after a negative productivity shock with training costs.



evidence. I use state-level analysis to provide some evidence on a theoretical "inaction region" for which firms might be hoarding a fraction of their employees when facing small negative shocks. I show that states that experienced larger oscillations in their unemployment rates tend to have a higher disparity between their expansionary and recessionary Okun's Law relationship.

Next, I use micro data to show that the "hoarded workers" tend to be of relatively higher skill since the unemployment pool becomes more educated on average only at troughs of recessions. With that evidence I turn my attention to a directed search model in which I introduce training costs. This component incentivizes firms to hoard workers when facing small negative shocks but they tend to over-react during large negative shocks.

Figure 9: Impulse response after a positive productivity shock with training costs.



I show that a model with only endogenous firms' exit is not enough to explain the state-dependence in the Okun's Law. I introduce training costs that generate labor hoarding in a directed search model. Labor hoarding shows up when firms face transitory or relatively small negative shocks and they try to save some fixed costs inherent from hiring and firing workers. The nonlinearity in the Okun's Law appears when a sufficiently large enough negative shock makes hoarding no longer profitable for a given set of workers.

Figure 10: Impulse response after a small negative productivity shock with training costs.

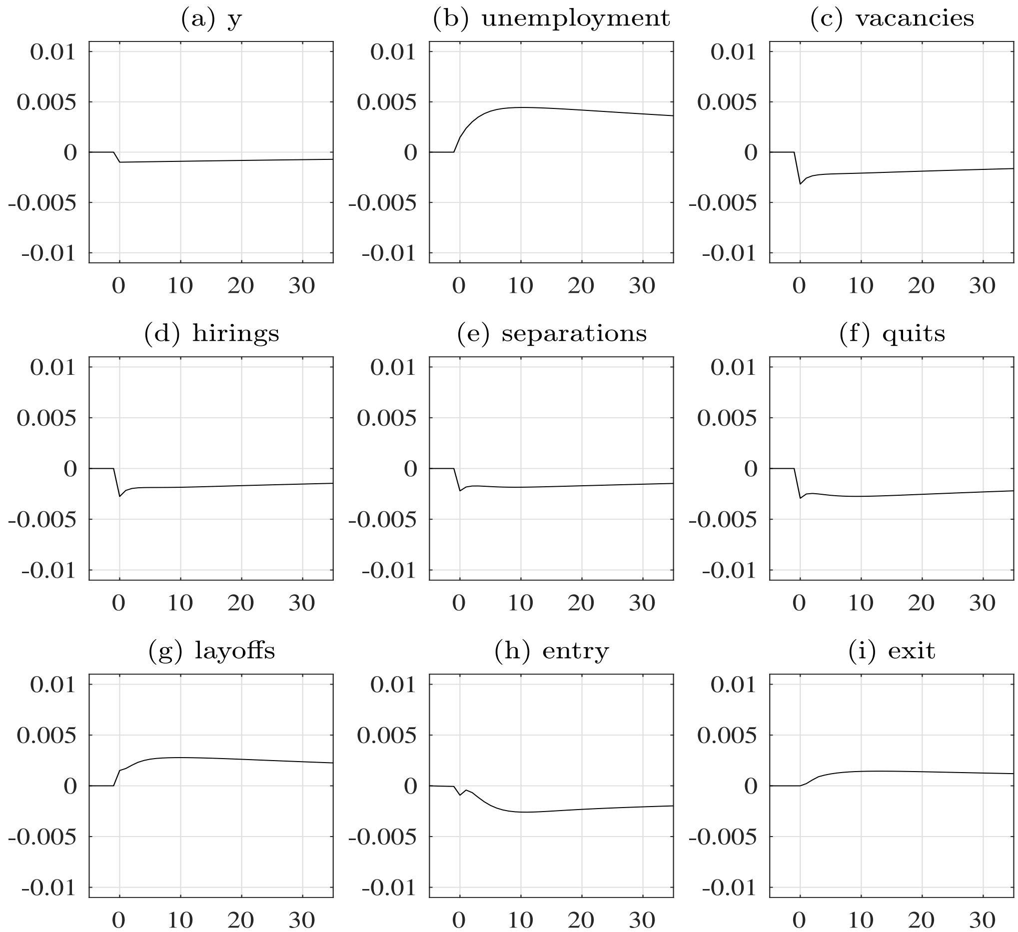


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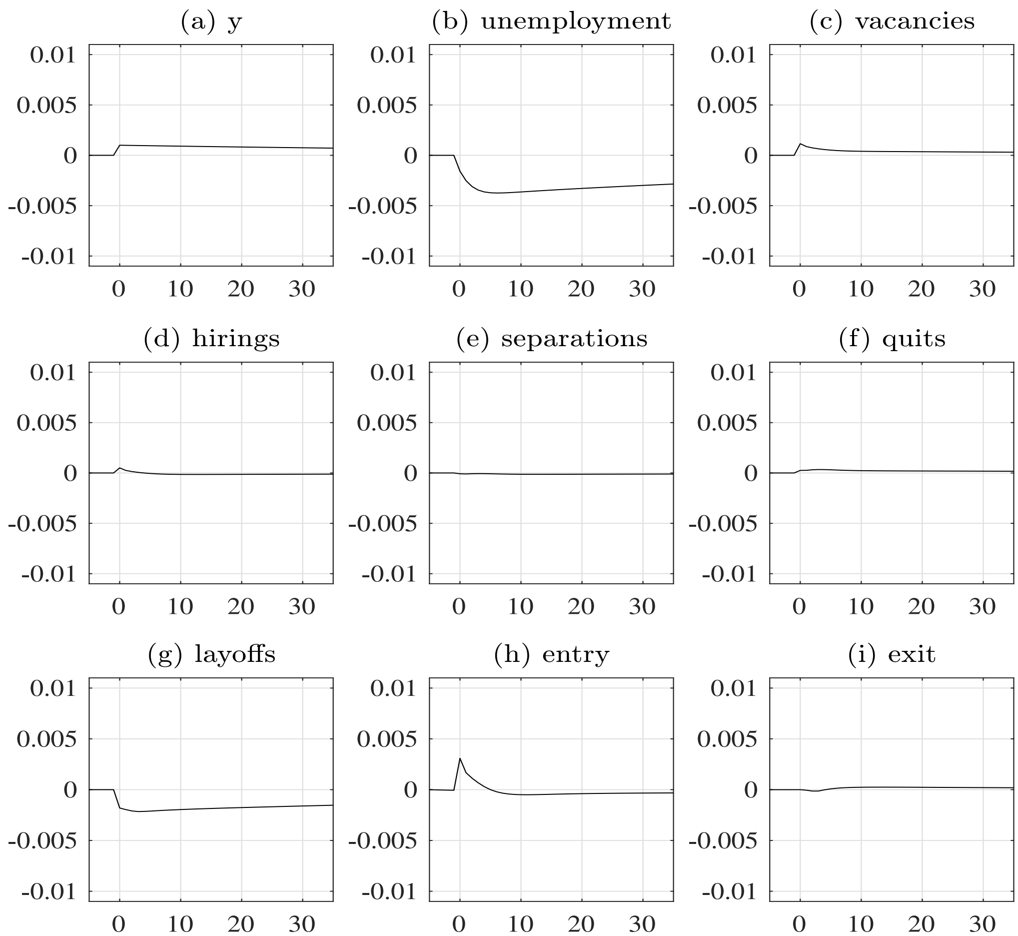
Figure 11: Impulse response after a small positive productivity shock with training costs.



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A Mathematical Appendix

A.1 Algorithm to identify recession periods

This algorithm is based on Dupraz et al. (2019). This algorithm aims to identify recessions according to the behavior of the unemployment rate. In this algorithm, I identify a recession as a number of months between identified peaks and troughs:

1. Define length T for a given unemployment rate time series;
2. Define threshold X which I use to identify peaks and troughs. I choose $X = 1.5$;
3. Define empty collections of *peaks* and *troughs*;
4. Set initial period: $t = 1$;
5. While $t < T$:
   (a) Set candidate for a peak $cp = t$ and update $t = t + 1$;
   (b) While $U_t < U_{cp}$, set new candidate for a peak $cp = t$ and update $t = t + 1$;
   (c) While $U_t \leq U_{cp} + X$:

i. If $U_t < U_{cp}$, then set new candidate for a peak $cp = t$ and update $t = t + 1$;

ii. Update $t = t + 1$;

(d) Save $peaks = [peaks, \quad cp]$

(e) Update $t = t + 1$;

(f) Set candidate for a trough $ct = t$ and update $t = t + 1$;

(g) While $U_t > U_{ct}$, set new candidate for a trough $ct = t$ and update $t = t+1$;

(h) While $U_t \geq U_{ct} - X$:

i. If $U_t > U_{ct}$, then set new candidate for a trough $ct = t$ and update $t = t + 1$;

ii. Update $t = t + 1$;

(i) Save $troughs = [troughs, \quad ct]$;

(j) Update $t = t + 1$;

6. Identify recessions as the months between a peak and its corresponding trough.

A Additional tables and figures

Figure A.1: Implication of the state dependent Okun's Law: NBER dates

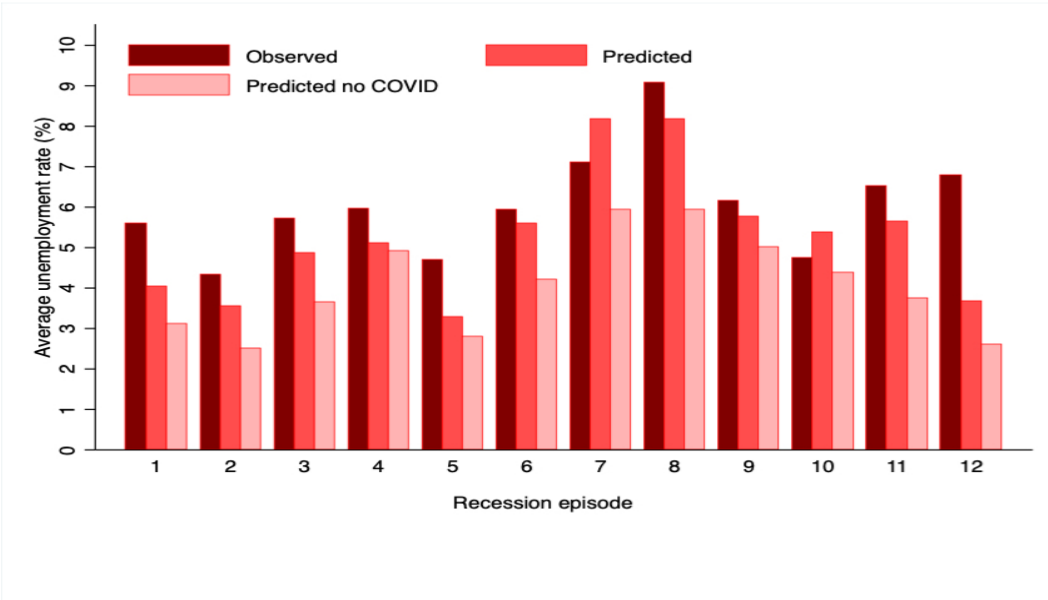

Figure A.2: Okun's law state dependence by state

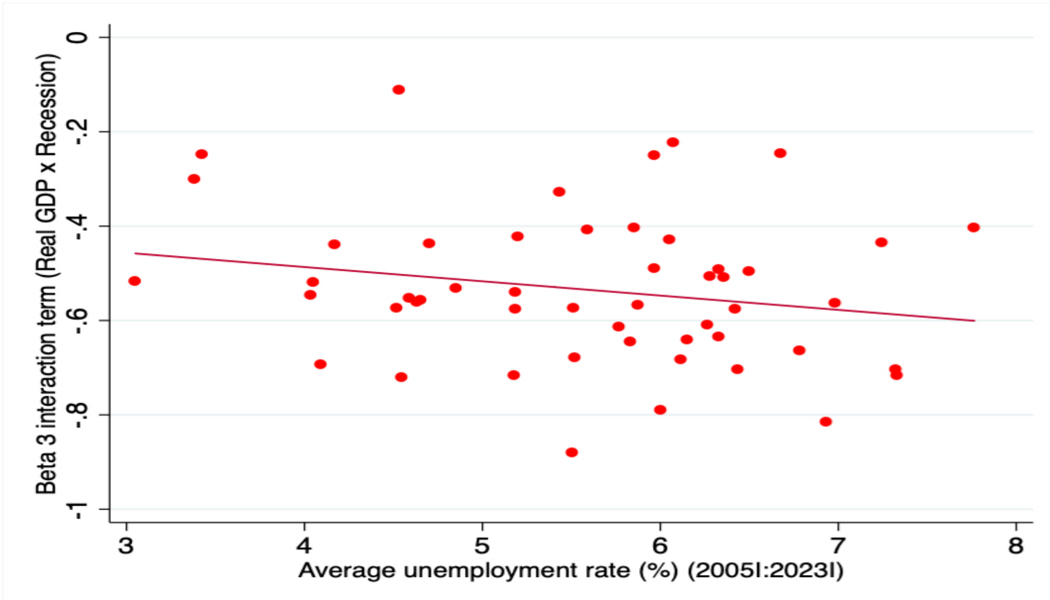

Figure A.3: Okun's law state dependence by state

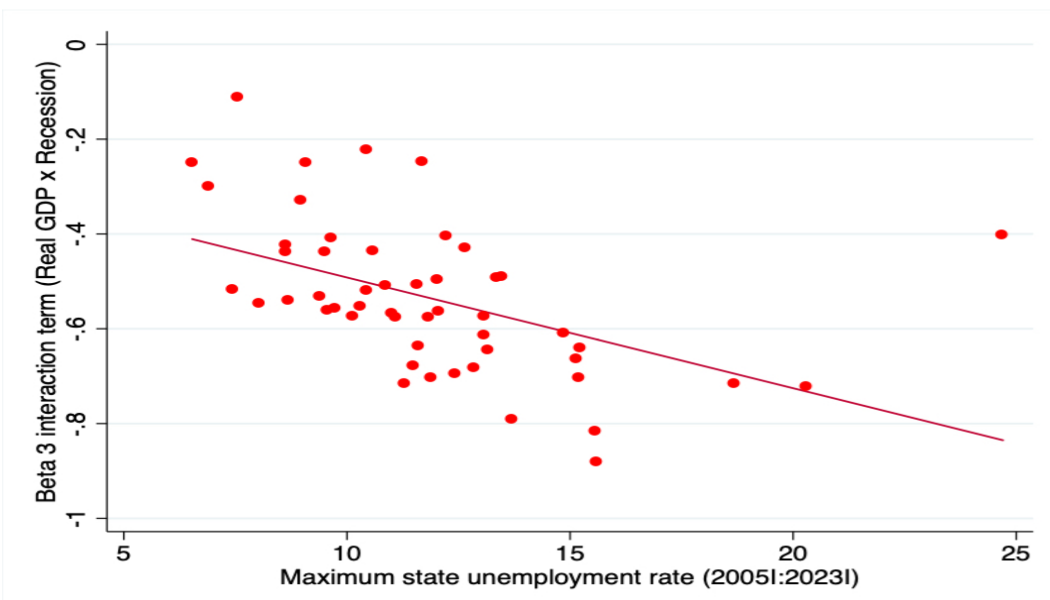

Table A1: Okun's law robustness

Variables	(1)	(2)
	$\Delta\hat{u}_t$	$\Delta\hat{u}_t$
$\Delta\hat{y}_t$	-0.478***	-0.143***
	(0.116)	(0.022)
Recession		0.513***
		(0.078)
Recession x $\Delta\hat{y}_t$		-0.468***
		(0.136)
Constant	0.374***	-0.036
	(0.107)	(0.026)
Observations	291	291
R-squared	0.605	0.722

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: I am running the same regression than the one shown in Table 2 but using quarter on quarter changes in deviations from the Non-Accelerating-Inflation-Rate-Unemployment (NAIRU) and quarter on quarter % growth of real GDP.

Table A2: Okun's law: NBER dates

Variables	(1) Aggregate	(2) NAIRU
	Δu_t	$\Delta \hat{u}_t$
Δy_t	-0.262***	
	(0.086)	
$\Delta \hat{y}_t$		2.503
		(3.073)
Recession NBER	0.260**	0.497***
	(0.116)	(0.1006)
Recession NBER x Δy_t	-0.456***	
	(0.198)	
Recession NBER x $\Delta \hat{y}_t$		-34.962**
		(16.434)
Constant	0.116	-0.166***
	(0.082)	(0.030)
Observations	295	292
R-squared	0.709	0.443

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A3: Unemployed pool demographics during trough times

Variables				
	Age	Some college	College degree	Highly paid Occupation
Trough	0.721***	0.016***	0.004	1.513***
	(0.118)	(0.002)	(0.003)	(0.150)
β_1 / Std. Dev.	0.35	0.29	0.08	0.96
Year fixed effects	Yes	Yes	Yes	Yes
Observations	564	564	564	564
R-squared	0.849	0.858	0.859	0.621

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1