Countercyclical Restructuring and Jobless Recoveries

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Abstract

In the past three recessions, two major features of the business cycle have changed. First, employment now lags output growth, leading to jobless recoveries. Second, average labor productivity (ALP) has become acyclical or even countercyclical. These facts are difficult to capture in standard models and this paper proposes a joint explanation for both facts. I develop a quantitative model in which firms streamline and restructure during recessions. The model captures the idea that firms grow fat during booms but then quickly restructure during recessions by laying off their unproductive workers. Firms then enter the recovery with a greater ability to meet expanding demand without hiring additional workers. This model endogenously generates a joint decline in the procyclicality of ALP as well as slower employment recoveries consistent with the aggregate data.

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1 Introduction

> "[Productivity growth] has enabled firms to meet the demand for their output without hiring workers.... Although other explanations for the jobless recoveries have played a role, in my view the productivity explanation is, quantitatively, probably the most important." - Ben Bernanke (2003)

Since the mid-1980s, two major features of the business cycle have changed: average labor productivity (ALP) has become markedly less procyclical and employment recoveries have become significantly slower. There is now a large and growing literature providing theoretical explanations for either jobless recoveries or the changing cyclical dynamics of ALP. [1] Typically, this literature has examined these facts in isolation from each other and candidate explanations are often inconsistent with the other fact. The central claim of this paper is that this isolated focus is a mistake as these two facts are intimately related and as a result new business cycle models should be consistent with both facts in a parsimonious way. In this paper, I formalize a single explanation for both facts.

Standard RBC models cannot explain why ALP is acyclical. If the model is driven by technology shocks, then labor productivity will be procyclical almost by construction. Even with other types of shocks, it is difficult to generate acyclical ALP because with a standard Cobb-Douglas production function and a competitive labor market, ALP is proportional to the wage. Thus, ALP can only be acyclical if real wages are too. Empirically, however, real wages are procyclical (Barsky, Parker and Solon, 1994; Haefke and van Rens, 2010).

I develop a quantitative model where firms take advantage of recessions as an opportunity to streamline and restructure. The model captures the idea that firms grow fat during economic expansions, but then quickly trim this fat by aggressively cutting costs in recessions. During booms, firms employ unproductive workers because learning about match quality takes time and because adjustment is costly. In recessions, firms shed unproductive workers causing ALP to increase endogenously. Firms then enter the recovery with a very productive workerforce and are reluctant to hire because it would diminish the quality of its workforce. I call this mechanism restructuring because it formalizes the conventional wisdom that firms

[1] Also see Aaronson et. al., 2004; Groshen and Potter, 2003; Shimer, Garin, Pries and Sims, 2014; 2012; Jaimovich and Siu, 2014; Gali and van Rens, 2014; Barnichon 2012; Morin 2014; Bachmann 2014.

survive recessions by focusing on cost cutting and boosting productivity. The model can quantitatively match both facts: it endogenously explains 30-50% of the decline in the procyclicality of ALP and generates much slower employment recoveries than implied by standard RBC model.

My starting point is a simple RBC model. I depart significantly from this framework by adding worker heterogeneity and the ability to selectively fire. Worker heterogeneity and selective firing create an additional restructuring margin that is central to my model. Second, I add employment adjustment costs. These costs, generate a trade-off between living with a low quality workforce and foregoing production while adjusting employment. This creates opportunities for intertemporal substitution and helps ensure that restructuring will be concentrated in recessions.

After calibrating the model, I perform several computational experiments. First, I show that the model without worker heterogeneity and labor adjustment costs cannot match the post-1984 labor market facts: ALP is strongly procyclical and there are no jobless recoveries. It can replicate the pre-1984 business cycle dynamics, but not the post-1984 ones. Then I add worker heterogeneity and selective firing and and show that this model generates slow employment recoveries and a large decline in ALP cyclicality. In other words, a model with adjustment costs, worker heterogeneity and selective firing can reasonably explain the post-1984 labor market facts.

Do firms selectively fire in reality? While it seems natural to hypothesize that firms do, this is a difficult question to answer empirically due to the lack of comprehensive worker level productivity data. I address this issue in two ways. First, I use novel worker level productivity and wage data for call center employees and show that there is much greater dispersion in individual productivity than in individual wages. In other words, there are many workers who are paid the same wage but have very different average productivities. This means, that at least for workers in these firms, there is a significant incentive to selectively fire. Second, I review a small but growing literature that documents evidence of selective firing and argue that it is a pervasive feature of the modern economy.

Finally, I discuss what changed in the 1980s. Through the lens of my mechanism there are two possible reasons that selective firing became more prevalent: either firms are more able to act on their knowledge of worker productivity or firms are more able to learn about worker quality. One reason that firms faced fewer external restrictions on their employment policies was due to the large decline in union power in the 1980s. This led to a sharp reduction in the restrictions firms faced when adjusting employment, which lowered firing costs and made it easier for firms to fire selectively. This led to a sharp reduction in the restrictions firms faced when adjusting employment, which lowered firing costs and made it easier for firms to fire selectively.[2] I test this hypothesis using variation from U.S. states. I show that states that had larger percentage declines in union coverage rates had larger declines in the in the cyclicality of ALP, consistent with my hypothesis. The union power hypothesis is also consistent with evidence from detailed industry studies. A recent paper by Dunne, Klimek and Schmitz (2010) shows that there were dramatic changes in the structure of union contracts in the U.S. cement industry in the early-1980s, which gave firms much more scope to fire workers based on performance rather than tenure. They show that immediately after these workplace restrictions were lifted, ALP and TFP in the industry increased significantly.

The second reason why restructuring could have become more prevalent in the 1980s is that employers became more able to learn about worker quality.[3] In recent years, many firms have invested enormous resources in information technology and that these investments have allowed firms to become more able to measure in real time the sales of their product lines, divisions, establishments, working groups and in some case individual workers. While I lack comprehensive evidence that firms use this information when they are deciding which products to discontinue or workers to lay off, I speculate that it is reasonable to think that they do.

This paper contributes to several literatures. It first relates to the literature on pit-stop theories of the business cycle (Davis and Haltiwanger, 1990; Aghion and Saint-Paul, 1993; Hall, 2000), the idea that recessions are times when productivity-improving activities are undertaken because of relatively low opportunity costs. The paper that is most similar to my own is Koenders and Rogerson (2005). In their model, organizational inefficiencies build up within a firm during booms because managers focus on growth, then get eliminated during recessions when managers switch their focus to removing inefficiencies. My research is importantly different in that it is in general equilibrium and it explores the quantitative implications of this class of models.

[2] Gali and van Rens (2010) also suggest that the decline in union power can help explain the decline in the procyclicality of ALP. In their model, less union power means lower adjustment costs which leads to decreased labor hoarding. However, this explanation does not explain why the recoveries have become jobless. Thus it must be the case that a decline in union power led the prevalence of selective firing to increase and not just to a decline in firing costs.

[3] This related but is conceptually distinct from the job polarization hypothesis discussed in Jaimovich and Siu (2014) and Morin (2014)

This paper also relates to the growing literature on jobless recoveries and the changing cyclical dynamics of ALP.[4] Typically, this literature has examined these facts in isolation from each other. Moreover, candidate theories tend to be inconsistent with the other post-1984 fact. For example, Bachmann (2014) argues that labor hoarding can help explain the 1991 and 2001 jobless recoveries. The problem with this explanation is that labor hoarding tends to make ALP more rather than less procyclical, in contrast to what we have observed in the data. Gali and van Rens (2014) present a model where the decline in the procyclicality of ALP is due to lower labor market frictions. In their model, smaller frictions to less labor hoarding, which makes ALP less procyclical. The difficulty with this explanation is that a decline in labor adjustment costs is inconsistent with jobless recoveries.

To my knowledge, there is only one other paper (Garin, Pries and Sims 2014) that also presents a unifying explanation for both jobless recoveries and the declining cyclicality of ALP. That paper's hypothesis is that, because of the Great Moderation, reallocation shocks have become relatively more important than aggregate shocks, so that now reallocative shocks play an increasingly important role during downturns. Increased reallocation from less productive to more productive sectors during recessions leads aggregate productivity to rise, helping to explain the decline in the cyclicality of ALP. If this reallocation takes time, it will take longer for employment to recover after a downturn providing an explanation for jobless recoveries. However, there are two potential issues with their explanation. First, the evidence that reallocation and mismatch have become relatively important in recent recessions is mixed. Recent work by Valetta and Kuang (2010) and Barnichon and Figura (2010) suggests that while there is evidence of mismatch during recessions, mismatch has not significantly increased since 1980s. Second, the Great Moderation was a global phenomenon: it occurred in every G-7 country (Summers, 2005). If the Garin, Pries and Sims hypothesis is correct, we should observe jobless recoveries and acyclical ALP in countries that also had Great Moderations. In the Appendix, I show that this is not something that we observe in the data. In fact, the coupling of jobless recoveries and acyclical ALP is only observed in the U.S., suggesting that we need a U.S. specific explanation for why these business cycle correlations changed in the mid-1980s.

The paper is organized as follows. In the next section, I document how the business cycle facts have changed. In Section 3, I present a simplified version of the model that conveys the main intuition. In Section

[4] Also see Aaronson et. al., 2004; Groshen and Potter, 2003; Shimer, 2010; and Jaimovich and Siu, 2014.

4, I build a general equilibrium model of firm dynamics. In Section 5, I add aggregate shocks and conduct the main policy experiment. In Section 6, I derive and test some implications of the model using firm level data from the Census LBD and ReLBD programs. In Section 7, I provide evidence that firms have significant scope to selectively fire and that since the 1980s, labor market institutions have shifted to allow for more selective firing. Section 7 concludes.

2 Aggregate Facts

The main source of data for the macro facts in this paper is the BLS labor productivity database. This database has quarterly information on output, total hours, employment and hours per worker from 1947 to the present. I follow the extant literature (Gali and van Rens, 2014) and use non-farm business as my main measure of output, however, the empirical results are robust to using GDP, all private business (including agriculture) and the non-financial sector instead. My preferred output series is constructed by excluding from GDP the following outputs: general government, nonprofit institutions, the farm sector, paid employees of private households, and the rental value of owner-occupied dwellings. Corresponding exclusions also are made to labor inputs. Hours and employment data for the major sector measures are drawn from the BLS Current Employment Statistics (CES) program, which provides monthly survey data on total employment and average weekly hours of production and nonsupervisory workers in nonagricultural establishments. Jobs rather than persons are counted. Weekly paid hours are adjusted to hours at work using data from the National Compensation Survey (NCS). I use total hours as my main measure of the labor input because it more closely corresponds to the labor measure in the model, since the model does not include a distinction between the bodies and hours per worker. I focus on the period 1951Q1-2015Q3. Since my focus is on labor market changes, I split the data into two sub-periods, pre-1984 (1951Q1-1983Q4) and post-1984 (1984Q1-2015Q3). The break date was chosen to be consistent with the existing literature (Gali and van Rens, 2014). None of the results are sensitive to this choice of break date.

I start by presenting evidence on the existence of jobless recoveries. Following the literature, I refer to jobless recoveries as a continued fall in aggregate labor input, accompanied by a continued increase in aggregate output (Aaronson et. al., 2004; Groshen and Potter, 2003; Bachmann, 2011). Figure 1 displays

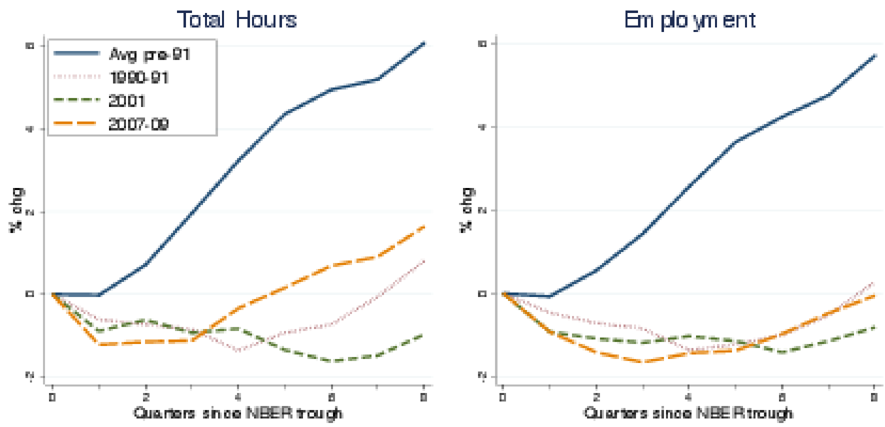

Figure 1: Jobless recoveries

total hours and employment following recessions, where both series are shown in log-deviations. I do not HP-filter the data since this filter is not reliable near the endpoints making inference about the behavior of labor input during the Great Recession difficult.[5] In each panel, all the series are normalized to zero at the NBER business cycle trough. The left panel of figure 1, shows that relative to pre-1991 recessions (solid line), total hours fell for multiple quarters as output recovered and did not recover to its pre-trough level for on average 6 quarters.

The right panel of figure 1 shows that the shift since pre-1991 recessions is even stronger for employment. This is because firms tend to increase hours per worker before they hire new workers (Bachmann 2014). In Appendix A, I show that the recent jobless recoveries are not driven by trend declines in certain sectors or by cyclically sensitive sectors. For example, I show that jobless recoveries remain even after the manufacturing and construction sector have been removed from the aggregate employment series.

The cyclical dynamics of ALP also changed in the mid-1980s (Gali and Gambetti, 2009; Barnichon, 2010; Gali and van Rens, 2014). The left panel of figure 2 shows the HP-filtered series of output and ALP.[6] I HP-filter both series because end point issues are less of a concern here since the change occurred in the middle of the sample period. The shaded regions denote NBER recessions. Casual observation suggests that both ALP and output were strongly positively correlated before the mid-1980s, but the correlation is

[5]The results are robust to HP-filtering the data.
[6]I use a smoothing parameter of 1600.

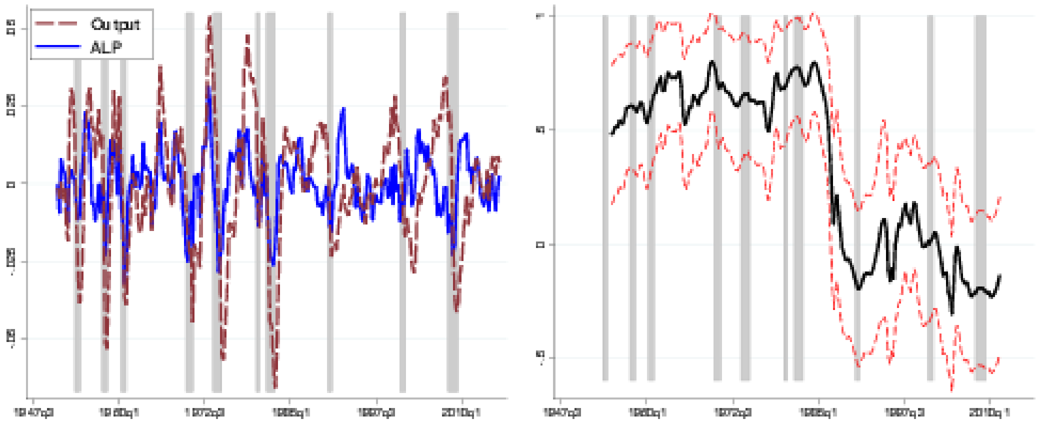

Figure 2: Correlation of output and ALP

much weaker now. The right panel confirms this observation. It shows the eight year centered rolling correlation between output and ALP along with 95% confidence intervals. Before the 1980s, the correlation between output and ALP was high and stable at around 0.65, whereas the correlation is near zero or negative starting in the mid-1980s. It is also clear that the decline in the correlation of output and ALP was sharp and dramatic. Three features of the data are responsible for this quick decline: the eight year window, the fact that there were recessions approximately ten years apart, and the fact that ALP was strongly procyclical in one (the 1982 recession) and strongly countercyclical in the other (the 1992 recession).

Since the decline is stark, I performed multiple robustness checks to ensure that this trend break was not driven by my choice of data set. Research on U.S. labor productivity is complicated by the fact that a variety of measures are used, many of which differ along several dimensions. Fortunately, a recent data set constructed by Brugemann, Hagedorn and Manovskii (2010) is useful for addressing this question. They construct a consistent data set of both labor input and output series and then examine many different combinations of assumptions in order to see which ones matter and which ones do not. While the magnitude and level of the decline varies across different measures of inputs and outputs, Table 5 in the appendix shows that the fact that there was a decline in the correlation of output and ALP during the 1980s is remarkably robust to the choice of data set. In particular, the decline is robust to using the aggregate employment measure from the household survey (CPS) as well as using GDP as the output measure.

	Pre-1984	Post-1984	Change
		Total hours	
HP	0.64***	-0.07	-0.71***
	(0.07)	(0.09)	(0.12)
BP	0.63***	-0.09	-0.71***
	(0.07)	(0.09)	(0.13)
		Employment	
HP	0.77***	0.33***	-0.43***
	(0.076)	(0.08)	(0.11)
BP	0.76***	0.35***	-0.40***
	(0.06)	(0.09)	(0.11)

SE in parenthesis. HP-filter with smoothing parameter of 1600.
Bandpass filter isolating periods [6-32]
Source: BLS Labor Productivity and Costs

Table 1: Correlation of Output and ALP

I also test formally whether the correlation between output and ALP changed in 1984. Table 1 displays the results: the change in correlations is strongly statistically significant.

In sum, there was a dramatic change in the cyclical behavior of labor and labor productivity in the mid-1980s. Since these two series are closely related – both are about the cyclical response of labor to output – and since these cyclical changes occurred at the same time it is natural to explore mechanisms that can simultaneously generate both aggregate facts. I discuss one such mechanism in the next section.

3 Simple model

In this section, I introduce a simple, two-period model to illustrate how worker heterogeneity, learning, and selective firing interact to generate sluggish employment recoveries and less procyclical productivity. I present the full, dynamic model in the next section but much of the core intuition can be seen in this pared down model.

Workers in the model are matched to firms and productivity is match specific. The fact that human capital is match specific plays an important role in keeping the general model tractable as will become clear in the next section. Abowd, Kramarz and Margolis (1999) and Mortensen (2003) find evidence consistent with this assumption using evidence from matched employer-employee data.[7] High and low productivity

[7] More empirical support comes from Jacobson, Lalonde and Sullivan (1993). They show that employees who lost their jobs in plant

matches produce efficiency units θ_H and θ_L, respectively, with $\theta_L \leq \theta_H$. When hiring, firms only observe the *average* match quality of a new hire, p, which is assumed to be constant in both periods.

The timing is as follows. In the first period, all firms are endowed with an initial TFP draw, z_1, and a certain number of employees, L_1, of whom a fraction α_1 are high productivity matches. The subscript denotes the time period. I work with a continuum of workers so the firm always knows α_1 precisely. At the end of the first period, firms learn the quality of its match with each of its workers. In the beginning of the second period, firms decide whether to hire new workers or fire existing ones.[8] I assume that employment adjustment is costless. After making this restructuring decision, firms produce a homogenous good using a Cobb-Douglas production function where the only input is the total efficiency units of labor, $\overline{\theta}L_2$. Here, $\overline{\theta}$ is the average match quality of all a firm's employees in efficiency units:

$$\overline{\theta}(\alpha_2) = \alpha_2\theta_H + (1 - \alpha_2)\theta_L$$

Because productivity is match specific, the outside of option of each worker is the same at all firms. I therefore assume that wages are the same for all workers and are equal to one in both periods. Together, these assumptions imply that high productivity matches are strictly preferable because, per efficiency unit, high productivity matches are cheaper for the firm. Firms would like to be able to identify and fire their low productivity matches. Finally, I assume that $\alpha_1 \geq p$. This assumption is (endogenously) satisfied in the fully dynamic model. In that model, a new firm, which has just hired by definition, has an average match quality equal to p. Firing (weakly) increases match quality because of selection.

Consider the restructuring decision of a firm that starts the second period with L_1 workers, fraction α_1 good matches, and TFP level z_1. The firm's TFP draw in the second period is z_2. Given α_1, L_1 and z_2, the

closings experienced large and persistent earnings losses, which is consistent with a significant component of human capital being match specific.

[8] This is a restriction, because a firm would be strictly better off if it could hire and fire within the same period. By firing all its known bad matches at the beginning of the period, a firm can always achieve a higher average match quality for a given workforce size. Firms are able to do this because they exchange certain bad matches with those that have a chance of being good. In the full model, firms will have the option of firing then hiring in the same period but will rarely do so, because they would have to pay the adjustment costs twice.

firm's optimal employment in the second period, L_2, solves:

$$\max_{L_2} z_2 \left[\overline{\theta}(\alpha_2)L_2\right]^{\gamma} - L_2$$

where $\gamma \in (0,1)$ and α_2 is given by the following weighted average:

$$\alpha_2 = \left\{ \begin{array}{ll} \alpha_1\left(\frac{L_1}{L_2}\right) + p\left(\frac{L_2-L_1}{L_2}\right) & \text{if hiring} \\ \alpha_1\left(\frac{L_1}{L_2}\right) & \text{if firing fewer than } (1-\alpha_1)L_1 \text{ employees} \\ 1 & \text{if firing more than } (1-\alpha_1)L_1 \text{ employees} \end{array} \right\}$$

Jobless Recoveries

Let's examine how average match quality at the firm affects the incentive to hire new workers. Suppose that productivity increases proportionately by τ so that $z_2 = (1+\tau)z_1$. Consider the homogenous worker model first ($\theta = p\theta_H + (1-p)\theta_L$). This is a natural benchmark to consider since the homogeneous worker model exhibits the same employment dynamics as the heterogeneous worker model when there is either no learning or no selective firing. In either case, average match quality for every firm is equal to $\overline{\theta}(p)$.[9] The growth rate of employment is:

$$g_e = \left[(1+\tau)^{\frac{1}{1-\gamma}} - 1\right] \tag{1}$$

A firm hires workers as long as $\tau > 0$, whenever TFP in the second period is greater than in the first period. Now consider the heterogeneous worker model with selective firing. In this case, the growth rate of employment is:

$$g_e = \left(\frac{\overline{\theta}(\alpha_1)}{\overline{\theta}(p)}\right)\left[\left(\frac{(1+\tau)\overline{\theta}(p)}{\overline{\theta}(\alpha_1)}\right)^{\frac{1}{1-\gamma}} - 1\right] \tag{2}$$

[9]When firms cannot learn about match quality, firms fire at random; conversely, if firms cannot lay off selectively, firm knowledge about individual employees cannot be used in termination decisions. The only difference between the two models is a scale factor, $\overline{\theta}(p)$, which affects the level, but not the growth rate of employment.

In the heterogeneous worker case (Equation 2), a firm only hires when τ exceeds a threshold, τ^* :

$$\tau^* = \frac{\overline{\theta}(\alpha_1)}{\overline{\theta}(p)} - 1 \tag{3}$$

We learn two things from examining Equation (3). First, $\tau^* > 0$. Assume for a moment that $\tau \in (0, \tau^*)$. Notice that this implies that TFP in the second period is strictly greater than TFP in the first period. Equation (1) shows that a firm in the homogeneous worker model would want to hire if it had this aggregate TFP draw, whereas Equation (3) shows that a firm in the heterogeneous model would want to lay off workers if it received this same TFP draw in the second period. This means that relative to the homogenous worker model, a firm needs a larger TFP shock in order to be willing to *not* layoff employees. The reason is because of firm learning and selective firing. At the end of the first period, the firm observes the exact quality of each worker, including the identity of all its worst matches. If $\tau \in (0, \tau^*)$, then the firm could increase its profits by shedding some of its low productivity ones. TFP must be high enough ($\tau > \tau^*$) to induce the firm to delay this restructuring process. The second point we learn from Equation (3) is that τ^* is increasing in α_1. In words, firms with an initially better matched workforce (higher α_1) need larger TFP to begin hiring than those with a more poorly matched workforce. The intuition is that new hires are on average less productive than incumbent workers, so that each additional hire dilutes average match quality, generating an additional margin of diminishing returns.

These two observations explain why the model with worker heterogeneity and selective firing is able to generate slow recoveries. After the recession, many firms have a well matched workforce because they recently laid off their productive employees. Now they need much higher productivity/demand to begin hiring again relative to the homogenous worker model.

Countercyclical Average Labor Productivity

ALP is defined in the model as Y/L where aggregate output and labor are defined as $Y = \int y_i$ and $L = \int L_i$ and $y_i = s\overline{\theta}^{\gamma} L_i^{\gamma}$ is gross output at firm i. Denote ALP initially and after selectively firing as $(Y/L)^i$ and $(Y/L)^f$ respectively. One can show that:[10]

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[10] $\frac{(Y/L)^f}{Y/L} = \left(\frac{\overline{\theta}(\alpha_1)}{\overline{\theta}(0)}\right)^{\gamma} \frac{1-\tau}{\left(1+g_f\right)^{1-\gamma}} > 1$. Because of selection, $\frac{\overline{\theta}(\alpha_1)}{\overline{\theta}(0)} > 1$. Then, using the definition of the growth rate when firing workers, $g_f = \left(\frac{\overline{\theta}(\alpha_1)}{\overline{\theta}(0)}\right) \left[\left(\frac{(1-\tau)\overline{\theta}(0)}{\overline{\theta}(\alpha_1)}\right)^{\frac{1}{1-\gamma}} - 1\right]$ implies that $\frac{1-\tau}{\left(1+g_f\right)^{1-\gamma}} > 1$.

In other words, ALP is higher after selectively firing. If layoffs are concentrated early in recessions, then the model can generate countercyclical ALP. The intuition is that firms shed their least productive workers rst, raising their average productivity and this composition e¤ect dominates the decline in ALP due to the fall in TFP.

This simple model illustrates how worker heterogeneity, learning and selective ring interact to allow the model to qualitatively generate jobless recoveries and countercyclical ALP. In order to evaluate whether these insights survive the introduction of dynamics, general equilibrium and adjustment costs, we need to investigate a quantitative version of this model.

4 Model

In this section, I describe a standard RBC model augmented with two types of worker quality and the ability to selectively fire.

4.1 Setup

Time is discrete and the horizon is infinite. The economy is inhabited by two kinds of entities: firms and consumers. Firms use labor to produce output. Consumers own firms, supply labor, and consume. There are perfectly competitive output and labor markets. One homogenous good is produced and sold. The price of output is the numeraire and is normalized to 1. The only price we have to keep track of is the wage of the workers.

Workers have heterogeneous match qualities. There are two types of matches, with efficiency units θ_H and θ_L . Match quality is specific to each firm-worker pair. In other words, a worker who is a bad match at one firm might be a good match at another firm. All matches are perfect substitutes. I work with a continuum of workers so the firm always knows precisely.

When firms hire, they do not know initially what the match quality of any individual worker will be. However, when they decide to lay off workers, they can do so selectively. The exact quality of each matched worker is known with certainty after one period. This is a stark assumption but it is a useful shortcut for a more micro-founded learning process. The probability that a newly hired worker is a good match is equal to p: This assumption is justified if work is an experience good: the firm only learns about the quality of the firm-worker match through production as in Jovanovic (1979). Since productivity is match specific, the composition over the potential match quality of the hiring pool is always constant.

Competitive markets pin down a unique wage. Since the quality of a match is specific to each firm/worker pair, good and bad workers are paid the same wage regardless of their history. This arises because each workers outside option is determined by what she could get paid if she worked at another firm (Felli and Harris, 1996). Because the labor market is competitive and human capital is firm/worker specific, workers cannot appropriate any of the match specific surplus (Becker, 1964).

Wage determination occurs in a similar manner as in a competitive model. The market clearing wage is the wage that clears the labor market.[11] The main difference is in this model the wage depends on both the exogenous and endogenous component of TFP rather than just the exogenous component. The wage depends on the endogenous component of labor (α) because the current level of worker quality affects the marginal incentive to hire new workers. In particular, the higher is the current level of a firms match quality the less the firm wants to hire new workers.

4.2 Firm's problem

The profit maximization problem can be written recursively as:

$$\begin{aligned} V\left(L,\alpha,z\right) = \quad & \max_{L'} \quad \exp\left(z\right)\theta\left(L,L',\alpha\right)\left(L'\right)^{\gamma} - wL' - \phi^{AC}\left|\left(\frac{L'-L}{L'}\right)\right| + \beta E\left[V\left(L',\alpha',z'\right) \mid \left(L,\alpha,z\right)\right] \\ s.t. \quad & \theta\left(L,L',\alpha\right) = \theta_H\alpha' + \theta_L\left(1-\alpha'\right) \\ & z' = \rho_z \ln z + \sigma_z\varepsilon, \end{aligned}$$

where α is the fraction of the good matches, L is last periods employment and $z$is the aggregate shock who dynamics are an AR(1) in logs. The term, $\phi^{AC}\left|\left(\frac{L'-L}{L'}\right)\right|$ is the adjustment cost. The novel aspect of this problem relative to standard RBC model is the introduction of heterogenous match quality and the ability

[11] While the two models are conceptually similar, the model with heterogenous workers is significantly more computationally burdensome to compute because labor demand today depends on expected labor demand and wages in the future. Thus in order to compute the labor demand curve, the value function must be solved and a fixed point for the wage schedule (which depends on all the state variables) must be found, which is what makes the problem longer to solve.

to selectively fire after learning a worker's quality.

firm hiring/firing decisions determine α', tomorrows proportion of good matches. The hiring case is straightforward. After hiring L' new employees, who are well matched with probability p, the proportion of matches that are of good quality is equal to:

$$\alpha' = \left(\frac{L}{L'}\right)\alpha + \left(\frac{L'-L}{L'}\right)p$$

a weighted average of its current size of the workforce as well as on its average match quality. This equation depends on both the current measure of employees as well as the current proportion of good matches. Another important point is that hiring dilutes the average quality of an firms workforce. This is true because in equilibrium, $\alpha \geq p$. Every entrant has $\alpha = p$ when first hiring, and then α (weakly) increases from there because of selective firing.

Selectivity combined with perfect substitutability (and the fact that all workers get paid the same wage) implies that when an firm lays workers off it gets rid of the worst matches first. The transition rule for α' :

$$\alpha' = \left\{ \begin{array}{c} \left(\frac{aL}{L'}\right) \text{ if } L - L' \in [0, (1-\alpha)L] \\ 1 \text{ if } L - L' \in ((1-\alpha)L(1-\delta), L] \end{array} \right\}$$

The top case shows how α' evolves if the firm only fires bad matches. This is possible if the firm wants to fire fewer than $(1-\alpha)L$ workers. If the firm desires to fire more than $(1-\alpha)L$ workers, then the firm has to fire some of its good matches as well and $\alpha' = 1$.

Finally, the firm also always has the option of not adjusting. In this case the problem is trivial with $h(\Gamma, z) = 0$ and $\alpha' = a$.

The addition of adjustment costs helps smooth out the representative firms labor decision. Without adjustment costs, firms often have the incentive to fire bad matches the period after they are hired because now these workers are known to be bad with certainty. If the firm faces a positive sequence of productivity innovations then the firm may choose to delay getting rid of these bad matches in order to be able to produce a lot while productivity is high. Adjustment costs provide an additional incentive to delay restructuring.

4.3 Household's problem

A representative consumer maximizes expected utility

$$U = E\left[\sum_{t=0}^{\infty}\beta^t\left(C_t - \frac{\phi}{1+\sigma_h}L_t{}^{1+\sigma_h}\right)\right]$$

choosing C_t, consumption of the numeraire good and L_t, total hours. $\beta \in (0,1)$ is the discount factor, $\phi > 0$ measures the disutility of labor supply and $1/\sigma_h$ is the Frisch elasticity of labor supply. The consumption good is perishable and there are no financial markets, so the consumer cannot save or borrow. The budget constraint each period is

$$C_t = w_t L_t + \Pi_t$$

where Π_t is the sum of all profits made in the economy and w_t is the wage rate, both expressed in terms of the consumption good numeraire.

The FOC are given by:

$$\begin{aligned}
\rho_t &= u_C(C_t, L_t) = 1 \\
w_t &= \frac{-u_N(C_t, L_t)}{\rho_t} = \frac{\phi L_t^{\sigma_h}}{\rho_t}
\end{aligned}$$

where ρ_t is the pricing kernel. Notice that the pricing kernel is pinned down by my assumption that the consumer has linear utility in consumption. This assumption is not innocuous but but is less concerning since the consumer's problem is static. This simplification enables me to apply the consumer discount factor β to the firms maximization problem.

4.4 Equilibrium

Equilibrium is standard in this model as there are only two markets that need to clear, the labor market and the goods market. The labor market clearing condition is

$$L'(L,\alpha,z) + \phi^{AC}\left|\frac{L'(L,\alpha,z) - L}{L'}\right| = L^S(L,\alpha,z)\,.$$

Symbol	Meaning	Value
p	prob. of good matches	0.8
θ_H	good match	1
θ_L	bad match	0.95
γ	power	0.64
β	discount factor	0.99
σ_h	inverse of frisch elasticity	2
(ρ_z, σ_z)	TFP process	$(0.95, 0.01)$
ϕ_{AC}	Adjustment cost parameter	.05

Table 2: Calibrated Parameters

and if that clears then the good market automatically clears by Walras law.

4.5 Calibration

I calibrate my model at quarterly frequency. Many of the parameters are standard. The disutility of labor ϕ is chosen to match a steady state labor supply of 0.6. σ_h, the inverse of the frisch elasticity, is set to be equal to 0.5. The discount factor is chosen to be $\beta = .99$ to match a 4% annual interest rate. The level of the adjustment cost is set to match the volatility of total hours. The curvature of the production function is set equal to 0.64 to be consistent with the labor share. Finally, the persistence and standard deviation of the aggregate TFP are set to standard parameter values.

There is less empirical guidance on how to set the parameters which govern the importance of worker heterogeneity and selective firing thus I choose to be conservative and explore robustness to reasonable changes in these parameters. I normalize the productivity of a high quality match equal to one and assume that low quality matches are only 5% worse. If the evidence on the productivity of call center employees presented in section 6, this seems to be a lower bound. I set the probability of a new hire being a good match to be equal to 0.8. Firms spend large amount of resources on hiring and thus it is reasonable to assume that the outcome of the hiring process is effective.

5 Results

I perform two experiments with three models: the standard RBC model and the model with heterogeneous workers with and without adjustment costs. The goal of the experiments is to evaluate whether each model can replicate the macro facts presented in Section 2.

5.1 ALP Results

The first experiment tests whether each of the models with aggregate shocks can match the decline in the procyclicality of labor productivity that was observed in the data. In order to compare the model simulated data with actual data, I compute the deviation from steady-state in the model for each variable ($log(X_t) - log(X_{ss})$) and compute the correlation between ALP and output.[12] I then compare the results to the HP-filtered empirical results reported in section 2. I report the level of this correlation for the data and all models in the second column of Table 3. The first two rows show the level of the correlation in the data for the pre and post 1984 period. As documented earlier, there was a large decline in the correlation between these periods, which is shown in the second column.

As is well known, the correlation between ALP and output is almost one in a standard RBC model. This happens for obvious reasons: ALP is directly proportional to the real wage in this model and the real wage inherits the cyclical properties of aggregate TFP, which is strongly procyclical. This is shown in column 3.

The fourth row shows the results for my model with selective firing. Relative to the RBC model, the model with heterogeneous workers and no adjustment costs (HW) reduces the correlation between output and ALP to 0.64, or 49% of the drop in the correlation that we observe in data. Given my assumptions, this comparison model is isomorphic to the RBC model, since if firms fire at random then $\alpha = p$ for all firms. This comparison highlights the role selective firing plays in generating the quantitative results. The fifth row shows what happens when adjustment costs are added to the heterogenous worker model in order to smooth out adjustment (HW + AC). As expected, adding adjustment costs increases the procyclicality of ALP because it induces an incentive to hoard labor. Nonetheless, this model is still able to generate a

[12] I use the log-deviation in the simulated data as the counterpart to the HP-filtered empirical data because the purpose of HP-filtering the empirical data is to remove trends which, by construction are absent in the simulated data. Canova (2007) argues this is the correct comparison to make and that HP-filtering the simulated data spuriously changes the correlation of stationary simulated data.

	$corr\,(Y, ALP)$	
	Level	Change
Data pre-1984	0.64	
Data post-1984	-0.07	-0.71
Baseline RBC	0.99	
HW	0.64	-0.35
HW + AC	0.74	-0.25

Table 3: Correlation between Output and ALP

significant drop in the procyclicality of ALP.

However, none of the models is not able to match the level of the correlation for the post-1984 period (0.64 vs -0.07). This failure is not surprising given that the model can only generate a rise in ALP during recessions through a composition effect. Since the aggregate driving force is a TFP shock, ALP, can only rise in recessions if endogenous match quality increases enough or labor demand declines enough.

In the appendix, I explore the robustness to changes in the worker productivity parameters. Increasing the productivity difference between high and low quality workers increases the models ability to generate a fall in the procyclicality of ALP while lowering the average quality of new hires moderately increases the procyclicality of ALP.

5.2 Slow employment recoveries

Next, I investigate each model's ability to generate slow employment recoveries and explore why these models are able to match the two new business cycle facts. Both heterogenous worker models induce significant history dependence and asymmetry relative to a standard RBC model. In other words, how labor in the model responds to a TFP shock depends a lot on the current levels of output and worker quality as well as whether the shock is positive or negative. It is this state dependence and asymmetry that allows the model to match to new cyclical facts.

First, I plot the impulse response of labor in the model to a positive 1% positive TFP shock when TFP is near it's median value. In order to ensure that the IRF is not driven by initial conditions, I plot the median IRF across 100 simulations. I plot this response for three models: the standard RBC model (RBC - solid line),

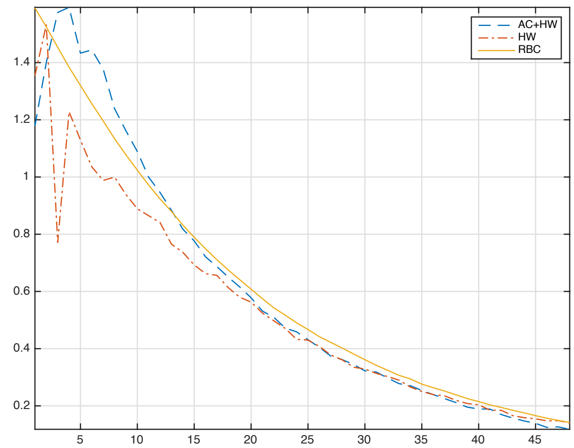

Figure 3: Response of Total hours to a 1% positive TFP shock in Steady State

the heterogenous worker model without adjustment costs (HW - dashed-dot line) and the heterogeneous worker model with adjustment costs (AC + HW - dashed line). This is shown in figure 3. As one can see, the response in all three models are of similar magnitudes and shapes. There are slight differences: the HW has a sharp decrease after the initial decrease and the HW is slightly humpshaped, but overall the response of labor in all three models is similar.

The response of the IRFs are very different after a boom which is shown in the left-side panel of figure 4. As expected, the response of labor to a 1% negative shock in the RBC model is almost the mirror image of the response of this model in figure 3. This is not surprising since nothing in this model delivers either state-dependence or asymmetry. The response of the HW model exhibits both. First, the response on impact is much larger than in the standard RBC model. This is because after a boom, firms have accumulated a lot of bad matches and the firm is happy to fire them in response to a negative TFP shock. This story is confirmed by examining the IRF of ALP to this shock which is shown in the right-side panel of figure 4. It is important to remember that ALP mechanically falls (which we see in the RBC model) in response to a negative TFP shock. However, for the HW we see the countervailing effect of worker composition. A negative TFP shock causes ALP to fall. However, the endogenous response of firms in this model is the fire their least productive workers which causes ALP to rise. The net effect is that ALP is less procyclical in the HW model. While the behavior of the AC + HW model would seem to contradict this logic, this is just a

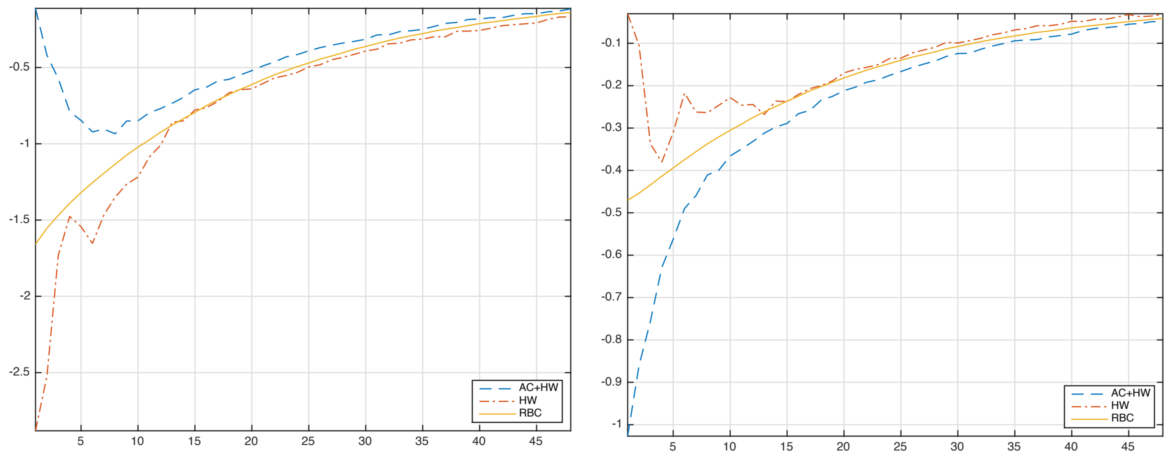

Figure 4: Response of Total Hours and ALP to a 1% negative TFP shock after a boom

feature of this particular boom. It is easy to find sample paths where the heterogeneous worker model with adjustment costs responds more than the RBC model and the HW after a negative TFP shock.

How does worker heterogeneity lead to slower employment recoveries than a standard RBC model? The key to understanding this is to remember that worker heterogeneity acts as an additional adjustment cost on the firms decision problem. Consider a firm that emerges from a recession only good matches and is thinking about hiring new workers. The simple model in Section 3 showed that firms with an initially better matched workforce (higher α) need larger TFP to begin hiring than those with a more poorly matched workforce. The reason is that new hires are on average less productive than incumbent workers, so that each additional hire dilutes average match quality. In other words, having a lot of productive workers gives a firm a new reason to delay hiring after a recession relative to a standard RBC model. It is this additional margin of diminishing returns that gives the model the ability to generate slow employment recoveries.

Figure 5 plots the IRF to a positive 1% TFP shock after a recession in all three models and shows that his intuition holds true. First, lets consider the simple RBC model. In that model, a firm responses immediately and monotonically to a 1% positive TFP shock. Now consider the how a heterogeneous firm would respond that has a well matched work force. Figure 5 shows that the response of labor input is much more muted relative to the standard model. The reason is this additional dimension of diminishing returns. Notice that this margin is quantitatively important even when there are no adjustment costs. This is because worker

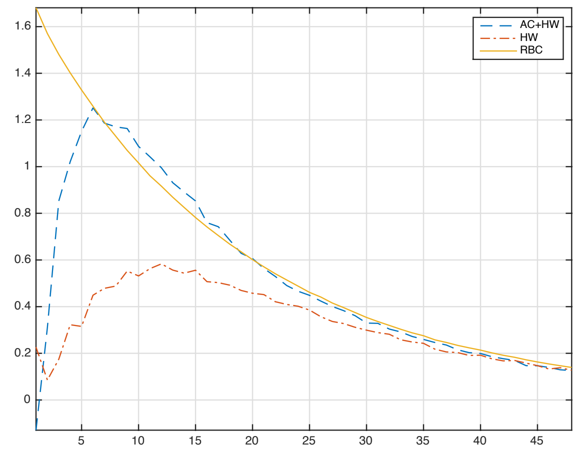

Figure 5: Response of Total hours to a 1% positive TFP shock after a Recession

heterogeneity acts as an endogenous adjustment cost that varies with the how well matched the work for is currently. In the limit, when all workers have quality equal to the expected quality of new hires ($\alpha = p$), the two models are identical. Finally, Figure 5 shows that the slow and hump-shaped response is also shared by the heterogeneous worker model with adjustment costs. In fact, this is the model's most robust results and it is the reason that the model generates slower employment recoveries than a standard model.[13]

6 Empirical implications of the model:

Add results once LBD and ReLBD results are finished and disclosed.

7 Discussion:

7.1 Scope of selective firing

Up to now, we have seen that a model where firms are able to learn about worker quality and selectively fire can match our new macroeconomic facts. But can and is there scope for selective firing? The former

[13]The fact that the HW + AC model responds more is not a general feature of the model. There are regions of the state space where the HW model responds more than the HW + AC model does to a positive TFP shock after a boom.

quesiton is easier to answer, at least in principle, because almost all employment in the U.S. is employment at will meaning the employer can end a workers employment contract at any time. The latter question is harder to answer due to the dearth of worker level productivity information. I now present some evidence for two firms where I can observe both wages and productivity and argue that at least for these firms - it is hard to know how generalizable this evidence is - there is significant scope for firms to want to selectively fire.

The data come from a consulting firm which tracks worker productivity and reason for separation for 37 call centers in the US.[14] This firm builds and deploys job testing software to large employers. Many of these employers are business process outsourcers (BPOs) that themselves provide a variety of business services (e.g., customer care, outbound sales, etc.) to their clients. The employees included in the dataset are all engaged in frontline service positions and paid on an hourly basis. In total there are 49,751 workers over December, 2010 through July, 2014 in the data set. Of these workers, 26,376 have left either because they quit or were fired by the end of our time-frame. These workers answer incoming calls either in the role of customer service or technical support. For more details see Berger, Gallen and Housman (2014).

For a small subset of these employees we observe both a measure of the worker's productivity and her wage. Our measure of productivity is the average number of calls a worker is able to resolve in an hour. From this, we construct a measure of average productivity for a worker over her tenure at the firm. The data include workers making calls for a variety of companies and providing either customer service or technical support. We combine this with information on the hourly wage rate as well as hours worked in each pay period for each worker in the firm in order to study the relationship between productivity and wages. Finally, we merge in limited information on worker demographics and aptitude.

Figure 6 displays the distribution of worker productivity and wages after controlling for observable characteristics.[15] The width if the bars is 1/4 of a standard deviation. The standard deviation of residual productivity is 1.7 calls per hour and standard deviation of residual wages is fifty cents. The average starting wage is $10 per hour and average wage growth is 16 cents per year based on a subsample of two plants for which we have data on wages paid to employees. This growth rate is slightly higher for more productive

[14]The data are discussed in more detail in Berger, Gallen and Housman 2014.

[15]Productivity is the residual after controlling for location and date fixed effects. Residual wages are residual of location, date of hire, and education level.

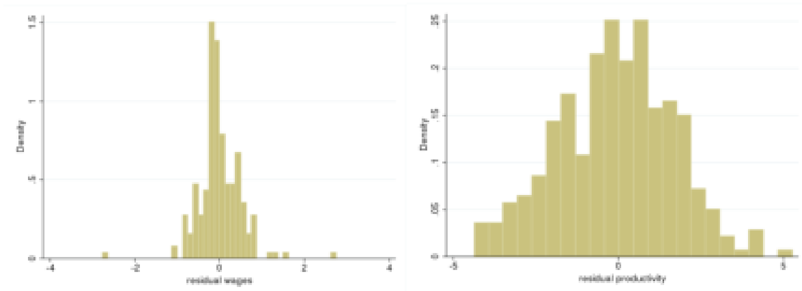

Figure 6: Dispersion in Wages and Worker Productivity

workers: a one standard deviation increase in worker productivity is associated with 2.4 cents higher annual wage growth. Notably, for workers hired in the time that we observe wages, the average starting wage is about one cent lower for a one standard deviation increase in productivity, though the difference is not significantly different from zero. 70% of the variation in starting wage is explained by month of hire, location and job fixed effects.

What immediately is obvious is that the variation in worker productivity is much larger than the variation in wages. In other words, there are many workers who have dramatically different productivities but are paid similar amounts. This suggests that firms have a strong motive to engage in selective firing by keeping the productive workers and letting go of the unproductive workers. Unfortunately, this data set is not very useful for examining the relationship between between layoffs and productivity because these call centers are in a traded sector and there was no significant aggregate demand shock during this time period since our data starts after the Great Recession is over. In the next section we review some alternative sources of evidences that firms do indeed selectively fire.

7.2 Evidence of selective firing

How prevalent is selective firing? There is significant anecdotal evidence that it is practiced by many firms. Jack Welch, perhaps the most influential CEO of the last 20 years, introduced a forced ranking system at General Electric in the early 1980s. Every year, each employee was ranked, those in the top 10% were given bonuses and those in the bottom 10% were red (Welch, 2001). Bewley (1999) in his landmark study of layoffs found that managers often discussed selective firing. Here is a representative quote from one of the managers he interviewed: "I consciously use layoffs to strengthen the quality of my work force...because I had difficulty finding people on the upside (1986-1989), there was a wide variation in the quality of my people. I wanted to cut my payroll and correct some of the problems brought on by hiring any warm body that came down the driveway."

Evidence from firm level data sets that include objective measures of worker quality confirm these anecdotes. Kahn and Lange (2010) show that receiving a lower performance score predicts employee exit. This is consistent with selective ring, however, Kahn and Lange are not able to distinguish between quits and layoffs in their data set, so it could be that ring is random, but quits are selective. Capelli and Conyon (2011) circumvent this problem by using more detailed data from a large Fortune 500 company. They show that receiving a lower score on a performance evaluation is strongly associated with a higher probability of being laid off.

More recently, Lazear, Shaw and Stanton (2014) analyze worker productivity data from one firm over the period 2006-2010 to understand why productivity at this firm increased during the Great Recession. There are two reasons why productivity could have increased: the firm fired more productive workers or that existing workers worked harder. They find that the increase in worker effort dominates, but they also find that selection plays a quantitatively important role.[16] Furthermore, a recent paper by Benson, Li and Shue (2014) uses workers employed in sales and also found evidence of selective dismissals using variation from the Great Recession. In particular, they find that in response to a negative industry level employment shock, lower productivity workers are more likely to exit the firm.

More generally, there is a burgeoning empirical literature documenting that firms respond to adverse trade shocks by terminating low performing establishments and product lines (Bernard and Jensen, 2007; Bernard, Redding and Schott, 2010; Arkolakis and Muendler, 2011). While the empirical context in these papers is exporters, it is likely that product switching and establishment shut downs are a more general feature of firm dynamics and one that leads to significant labor market reallocation.[17] The employees who are laid off in response to these negative shocks are not low quality per se, rather they just happen to produce a product for which there is little demand. Thus, a more holistic interpretation of what constitutes

[16] One reason their result might be a lower bound on selection is that their data does not allow them to separate layoffs from quits.

[17] For example, the USPS is shutting down 3600 post o ces around the U.S., 3000 of which had less than $27,500 in annual sales (Courson and Liberto, 2011)

restructuring suggests that selectively "pruning" is quite likely a pervasive feature of reality.

7.3 Has the prevalence of selective firing increased?

Figure 2 shows that ALP went from being strongly procyclical to mildly countercyclical in only 10 years during the 1980s. What changed? This paper has argued that one potential explanation is that the prevelance of selective firing has increased. Unfortunately, the lack of comprehensive time-series data on worker productivity makes providing direct evidence of this inherently speculative, however there is some indirect evidence. Farber and Hallock (1999) show that the stock market reaction to layoffs has become more positive over time since the 1970s. In particular, it was negative in the 1970s and has become positive more recently. They interpret this as evidence that firms have become more effective at creating value when they conduct layoffs. Kosovich (2010) updates the classic "Layoffs and Lemons" paper of Gibbons and Katz (1994) and argues that the wage penalty from a layoff has increased in the 1990s relative to the early 1980s.[18] Both of these facts are consistent with more prevalent use of selective firing.

In order to be able to selectively fire you must a) be able to act on your knowledge of worker productivity and you must be able to measure worker quality. One candidate explanation that contributed to (a) is the decline in union power.[19] This story lines up well with the observed decline in the procyclicality of ALP. Farber and Western (2002) document a sharp decline in the number of union certification elections in the early 80s. They interpret this as evidence for an "unfavourable political climate which raises the costs of unionization", induced by Reagan's policies and in particular his handling of the air-traffic controllers' strike in 1981. Union contracts often include legal restrictions which limit the ability of a firm to adjust its workforce, in particular rules governing layoffs. Abraham and Medoff (1984) find that 92% of union firms have written rules to deal with permanent layoffs while only 24% of nonunion firms have such written layoff policies, and that 58% of nonunion firms have a practice of sometimes laying off a more senior worker if

[18]Gibbons and Katz (1994) analyze the 1984-86 Displaced Workers Survey and find that the wage penalty for being laid off was 13%. That is, the change in log weekly earnings from the former to current job was -13%. Kosovich (2010) finds using data the mid-1990s Displaced Workers Survey that the wage penalty is now 17%.

[19]Gali and van Rens (2010) also suggest that the decline in union power can help explain the decline in the procyclicality of ALP. Less union power means lower adjustment costs which leads to decreased labor hoarding. However, this explanation does not explain why the recoveries have become jobless. Closely related to the union power hypothesis is the "disposable worker hypothesis" of Gordon (2010). He argues that there was an increase in managerial power and a decline in labor power that contributed to both the rise in inequality and the increasingly cyclically sensitive labor market that we have observed. A closely related explanation is that there was a dramatic shift in corporate philosophy towards maximizing shareholder value, especially since 1990 (Sinai 2010).

a junior worker is believed to be worth more on net, as compared to 17% of union employers. Further suggestive evidence comes from Dunne, Klimek and Schmitz (2010). They show that there were dramatic changes in the structure of union contracts in U.S. cement industry in the mid-1980s which gave firms much more scope to fire workers based on performance rather than just tenure, and as a result ALP and TFP in the industry dramatically increased.

In order to address the question more directly, I examine cross-state variation in union coverage rates, the percentage of the workforce covered by collective bargaining agreements. I test whether states which had larger percentage declines in coverage rates had larger declines in the correlation of output and labor productivity. I use annual output and employment data for each state from the BEA's Regional Economic Accounts and state level information on union coverage rates from the CPS.[20] Since I lack a measure of total hours by state, my measure of labor productivity is output per worker. My estimating equation is:

$$(\rho_{i,post95} - \rho_{i,pre85}) = \alpha + \beta \log(\overline{UC}_{i,post95} / \overline{UC}_{i,pre85}) + \epsilon \tag{4}$$

Here, $\rho_{i,post95}$ and $\rho_{i,pre85}$ denote the correlation between output and output per worker for state i in the post-1995 and pre-1985 periods, respectively. These dates were chosen to ensure that the correlation was computed using the same number of observations in each time period, but the results are robust to reasonably different choices. The correlations were computed using logged and HP-filtered data with a smoothing parameter of 6.25. $\overline{UC}_{s,post95}$ and $\overline{UC}_{s,pre82}$ are the mean union coverage rates for state i in the pre and post periods. The coefficient β is the object of interest. It captures the association between the change in the level of the correlation between output and output per worker and the percentage change in the union coverage rates from the pre-1985 to the post-1995 eras. The union power hypothesis predicts that $\beta > 0$: states which had larger percentage declines in unionization rates should have larger declines in the level of the correlation between output and labor productivity.

I split my sample and estimate Equation (4) in right-to-work and non right-to-work states separately.[21] It is common in the empirical literature on union power to characterize right-to-work states as "pro-business" and non right-to-work states as "anti-business" (Holmes, 1998), though this decomposition is obviously a

[20]The unionization data are available at unionstats.com.

[21]Results for using the whole sample are reported in the appendix.

	Right-to-work states		Non right-to-work states	
	Change in corr(Y,Y/E)	% change in corr(Y,Y/E)	Change in corr(Y,Y/E)	% change in corr(Y,Y/E)
$\widehat{\alpha}$	-0.218	-0.026	0.231	0.341
	(0.392)	(0.648)	(0.209)	(0.335)
$\widehat{\beta}$	0.095	0.528	0.902**	1.257**
	(0.468)	(0.812)	(0.338)	(0.553)
Observations	21	21	29	29
R-squared	0.001	0.019	0.127	0.100

Robust SE in parentheses. All observations weighted by mean employment pre-1985. Dependent variable is union coverage rates. Source: BEA's Regional Economic Accounts and Current Population Statistics

Table 4: Regression results: Union power and the decline in ALP

coarse measure at best. If the union power hypothesis is true, one would expect to observe a statistically stronger relationship between the decline in union coverage rates and the change in the cyclicality of ALP in non right-to-work states because these are the states where unions were historically more powerful. The results are shown in Table 4 and are consistent with the union power hypothesis. I weight each observation by the average employment per state in the pre-1985 period. There is no significant statistical relationship between the change in union coverage rates and the change in the level of the correlation between output and ALP in right-to-work states, but a strong relationship in the non right-to-work states. This is consistent with the argument that a decline in union power lead to an increase in the frequency of selective firing since the 1980s.[22]

Finally, my model provides an alternative mechanism that can explain why restructuring became more prevalent in the 1980s - employers become more able to learn about worker quality. For my restructuring margin to operate, firms must both be able to learn about worker quality and be able to selectively fire. I have chosen, for empirical reasons, to focus on the case where the speed and scope of employer learning are held constant while the ability of firms to selectively fire is increased, however, I think it is quite reasonable to believe that firms have also become more able to measure worker quality.[23] Anecdotally at least, we know that firms have invested enormous resources in information technology and that these investments have allowed firms to become more able to measure in real time the sales of their product lines, divisions, establishments, working groups and in some case individual workers. While we lack compre-

[22]A decline in union power could also lead to a decline in adjustment costs more generally. While this could explain some of the decline in the procyclicality of TFP, it cannot explain jobless recoveries (Bachmann 2014).

[23]The fact that more workers are employed in the service sector, where is it on average more difficult to identify the quality of the worker, is a countervailing effect.

hensive evidence that firms use this information when they are deciding which products to discontinue or workers to lay off, I think it is reasonable to think that they do. At the very least, providing comprehensive evidence of whether firms use this technology in making termination decisions is an interesting topic for future research.

8 Conclusion

Since the mid-1980s, average labor productivity has become less procyclical at the same time as employment recoveries have become markedly slower. In this paper, I argue that these two facts are intimately related and argue that explanations of either phenomena should be consistent with the other. Moreover, these new business cycle facts present a strong challenge to standard business cycle models since the baseline models are typically inconsistent with both facts.

In this paper I develop a model that can match these two facts. The model captures the idea that firms grow "fat" during booms but then aggressively restructure their workforce during recessions. In the model, firms employ unproductive workers because learning about match quality takes time and because adjustment is costly. In recessions, firms shed unproductive workers causing ALP to increase endogenously. Firms enter the recovery with a very productive workerforce and are therefore reluctant to hire because it would diminish the quality of its workforce.

I calibrate a standard RBC model augmented with two types of worker quality and the ability to selectively fire. I find that the model can generate a large decline in the procyclicality of ALP (relative to the model without selective firing) and can generate slow employment recoveries after recessions. In other words, these two features go a long way in helping standard business cycle models reproduce these new business cycle facts.

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Appendix

Decline in the cyclicality of ALP

I show that the decline in the procyclicality of ALP is robust to using different output and employment measures, occurs most strongly in the U.S. and is not driven by a change in entry and exit dynamics. Following Brugemann, Hagedorn and Manovskii (2010), I use the following shorthand to refer to the possible permutations of data source, labor input, sector and filter.

1. Data source: I use "cps" and "lpc" to refer to data from the Current Populations Statistics (BLS household survey) and Labor Productivity and Costs (BLS Establishment survey), respectively

2. Sector: I use "nfb" for nonfarm business and "all" for total economy

The results are shown in Table 9. The first three columns show the correlation between output and output/hour for the pre-1984, post-1984 as well as the change in the correlations. In every case, the change in the correlations between the sub-periods is statistically significant and quite large. The fifth column examines whether we can formally detect a trend break in the correlations without specifying the break point ex-ante. To do this I implement the procedure described by Andrews and Ploberger (1994). For the LPC measures of labor input, one can reject the null of no structural break at the 1% significance level. The results for CPS measures of labor input are less clean, however, one can reject the null of no structural break at the 10% level for the nonfarm-business productivity measure.

The Conference Board collects annual data on GDP and total hours across countries. I use this data to analyze whether the decline in the procyclicality in ALP during the mid-1980s was unique to the U.S. among G7 countries. The results are shown in in the first three columns of Table 10. The first and second columns show the pre and post 1984 levels of the correlation between HP-filtered output and ALP. I used a smooth parameter of 6.25 though the results are not sensitive to this choice. They show that while the decline in procyclicality of ALP occurred in 6 of the 7 G-7 nations, the decline was only statistically significant in the U.S. As a robustness check, I also allow for the two time periods to vary by country. In particular, I choose the end of the first period to be the year in which the Great Moderation started in that country using the country specific dates from Summers (2005). The results are shown in the last three columns of Table 10. The main difference between the baseline results is that now the decline in the correlation is significant for France as well as the U.S. All the other results are consistent across the two specifications. Overall then, Table 10 provides suggestive evidence that we should explore U.S. specific explanations - as opposed to global explanations - when seeking to explain what changed in the mid-1980s.

Jobless Recoveries

It is often argued that the jobless recoveries are merely an artifact the secular decline in manufacturing employment. To show that this is not the case, I recreate the standard jobless recovery figures excluding manufacturing (RHS of Figure 7) and excluding manufacturing and construction employment (LHS of Figure 7). The series come from the Current Establishment Survey. All series are at a quarterly frequency and seasonally adjusted. In total, Figure 7 shows that removing manufacturing (and construction) attenuates jobless recoveries but it does not remove them altogether, especially for Great Recession.

	Correlation with Output				Trend break statistics
	Pre-84	Post-84	Change	Obs	Andrews/Ploberger (1994)
LPC (nfb)	0.64***	-0.02	-0.67***	254	-7.48***
	(0.06)	(0.12)	(0.13)		(1987Q2)
CPS (nfb)	0.96***	0.25**	-0.70***	138	-4.41*
	(0.10)	(0.10)	(0.14)		(1987Q3)
LPC (all)	0.51***	0.05	-0.46***	246	-6.38***
	(0.06)	(0.14)	(0.15)		(1987Q2)
CPS (all)	0.57***	0.02	-0.55***	252	-3.33
	(0.06)	(0.13)	(0.14)		(1980Q2)

Standard Errors in parenthesis. NFB is "non-farm business" and "all" is the entire US economy
See Brugemann, Hagedorn and Manovskii (2010) for details about the data construction

Table 5: Robustness checks: correlation between output and ALP

	Correlation with Output					
	Pre-84	**Post-84**	**Change**	**Pre-GM**	**Post-GM**	**Change**
USA	0.46***	-0.27	-0.73**	0.46***	-0.27	-0.73**
	(0.14)	(0.26)	(0.29)	(0.14)	(0.26)	(0.29)
Japan	0.83***	0.69***	-0.14	0.78***	0.72***	-0.06
	(0.13)	(0.15)	(0.20)	(0.14)	(0.12)	(0.23)
UK	0.47**	0.37**	-0.10	0.53***	0.35*	-0.18
	(0.18)	(0.19)	(0.26)	(0.16)	(0.20)	(0.23)
France	0.65***	0.35**	-0.30	0.85***	0.30*	-0.55**
	(0.17)	(0.17)	(0.24)	(0.15)	(0.16)	(0.22)
Italy	0.84***	0.68***	-0.16	0.74***	0.71***	-0.03
	(0.13)	(0.18)	(0.22)	(0.14)	(0.17)	(0.25)
Canada	0.37**	0.47***	0.10	0.37**	0.47**	0.10
	(0.16)	(0.14)	(0.21)	(0.15)	(0.20)	(0.19)

Data are from the Conference Board. The data spans 1960-2009.
Data exclude Germany because reunification leads to trend breaks in the data in 1989.
Great Moderation (GM) start date for each country taken from Summers (2005)

Table 6: Correlation of output and ALP (G7 Nations)

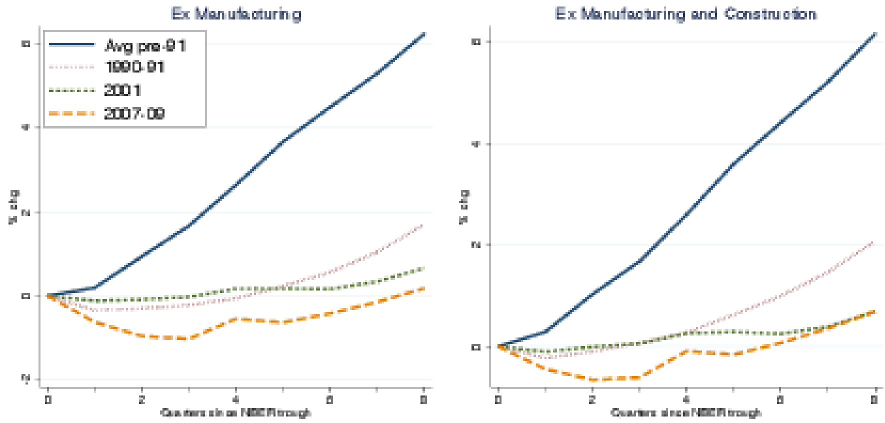

Figure 7: Jobless recoveries Robustness

	$corr\,(Y, ALP)$	
	$p = .8$	$p = .6$
$\theta = .95$	0.74	0.89
$\theta = .9$	0.63	0.88

Table 7: Robustness of Worker Heterogeneity Parameters and $Corr\,(ALP, Y)$

Model Robustness

In this section I show how the correlation between ALP and output in the heterogeneous worker model with adjustment costs depends on the parameters of worker productivity, in particular I vary the relative quality of the low quality match to be either 5% percent less productive (the baseline) to be 10% less productive. The columns vary the average quality of new hires. This is shown in table 7. The results are reasonably robust reasonable changes in these parameters though there is some variation. As the quality of the lower quality match decreases, the average correlation decreases. More interestingly, lowering the average quality of new hires tends to raise the productivity of new matches. This because when new workers are of such low average quality, firms have a significant incentive to never have any poor matches.

Robustness of Union Evidence

The results are shown in Table 3. I weight each observation by the average employment per state in the pre-1985 period. The observations are weighted because I want to capture the average effect of the decline in unionization and I do not want the results to be unduly influenced by small state outliers.[24] The first column presents the results where the change in correlation is in levels. Consistent with the union power hypothesis, the estimate $\widehat{\beta}$ is significantly positive. A 50% decline in the union coverage rate (close to the mean decline for this time period) is associated with a 0.32 decline in the level of the correlation between output

[24] The results are robust to weighted the observations by union coverage and membership levels in the pre-1982 period.

	Union coverage rates		Union membership rates	
	Change in corr(Y,Y/E)	% change in corr(Y,Y/E)	Change in corr(Y,Y/E)	% change in corr(Y,Y/E)
$\widehat{\alpha}$	0.083	0.182	0.050	0.138
	(0.192)	(0.291)	(0.186)	(0.281)
$\widehat{\beta}$	0.565*	0.878**	0.455*	0.723*
	(0.292)	(0.432)	(0.253)	(0.377)
Observations	51	51	51	51
R-squared	0.079	0.084	0.069	0.076

Robust SE in parentheses. All observations weighted by mean employment pre-1985
Source: BEA's Regional Economic Accounts and Current Population Statistics

Table 8: Regression results: Union power and the decline in corr(Y,Y/E)

and output per worker. The second column presents the results when the dependent variable ($corr(Y, Y/E)$) is in percentage changes rather than levels. Once again, the estimate $\widehat{\beta}$ is positive and significant, which is supportive of the union power hypothesis. As an additional robustness check, the third and fourth columns of Table 7 show the results when using union membership rather than union coverage as the measure of union power. The qualitative results are unchanged.

The results are shown in Table 6. I weight each observation by the average employment per state in the pre-1985 period. The observations are weighted because I want to capture the average effect of the decline in unionization and I do not want the results to be unduly influenced by small state outliers.[25] The first column presents the results where the change in correlation is in levels. Consistent with the union power hypothesis, the estimate $\widehat{\beta}$ is significantly positive. A 50% decline in the union coverage rate (close to the mean decline for this time period) is associated with a 0.32 decline in the level of the correlation between output and output per worker. The second column presents the results when the dependent variable ($corr(Y, Y/E)$) is in percentage changes rather than levels. Once again, the estimate $\widehat{\beta}$ is positive and significant, which is supportive of the union power hypothesis. As an additional robustness check, the third and fourth columns of Table 7 show the results when using union membership rather than union coverage as the measure of union power. The qualitative results are unchanged.

[25]The results are robust to weighted the observations by union coverage and membership levels in the pre-1982 period.