Skill Loss, Job Mismatch and the Slow Recovery from the Great Recession[*]

Karl Walentin[†] and Andreas Westermark[‡]

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Abstract

In this paper we quantify the importance of human capital dynamics and job mismatch in slowing down recoveries from recessions, in particular the Great Recession. The basic question we ask is to what degree i) human capital dynamics induced by skill loss during unemployment and ii) job mismatch (low match quality) contributed to the slow recovery from the Great Recession, in particular the low post-2009 growth in GDP, labor productivity and real wages. Mismatch has increased because workers that lost their jobs in the recession tend to be less well matched compared to their pre-recession jobs. We find that the increase in unemployment during 2007-2009 had long-lasting effects through the skill loss it induced, mainly in terms of increased unemployment and reduced GDP.

Keywords: Search and matching, labor market, human capital, job ladder, on-the-job search.

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[†]Research Division, Sveriges Riksbank. E-mail: karl.walentin@riksbank.se.
[‡]Research Division, Sveriges Riksbank. E-mail: andreas.westermark@riksbank.se.

1 Introduction

In this paper we quantify the importance of human capital dynamics and job mismatch in slowing down recoveries from recessions, in particular the Great Recession. The basic question we ask is to what degree i) human capital dynamics induced by skill loss during unemployment and ii) job mismatch (low match quality) due to search frictions has contributed to the slow and incomplete recovery from the Great Recession, in particular the low post-2009 growth in GDP, employment, labor productivity and real wages. These variables have been growing substantially below trend since the 2008-2009 crisis, see e.g. Fernald, Hall, Stock and Watson (2017) or BLS (2017). This slow and incomplete recovery from the Great Recession is not only a U.S. phenomenon but is present in most OECD countries, although for concreteness we only analyze the U.S. in this paper.

The two above mechanisms are supported by microdata findings. First, regarding skill loss during unemployment, Yagan (2017) establishes a strong link between local shocks to employment growth during the Great Recession, 2007-2009, and the 2015 employment rates of workers exposed to these shocks and that this effect is caused by depreciation of general human capital during non-employment spells. Second, regarding mismatch, Haltiwanger et al. (2018) documents the cyclicality of job-to-job flows. They find that such flows are highly procyclical and generally go to higher paying firms, plausibly firms with higher productivity. This cyclical pattern was particularly strong in the Great Recession, when the jobs flows to such firms collapsed almost entirely. This type of sullying effect of recessions was noted by Barlevy (2002). Capturing the aggregate productivity effects of job-to-job flows requires modelling a job ladder, i.e. allowing for on-the-job search (OJS) and heterogeneity in productivity between jobs.

In addition to the effects on GDP and average labor productivity (ALP), the above two mechanisms also affect real wage growth. Real wage growth during the post-crisis period has remained subdued compared to historical patterns. In particular, it has been lower than what is normally observed at this point in the cycle or for the level of unemployment that has prevailed, see BLS (2017). One component of the lower wage growth is due to the low growth in labor productivity. To be specific, the mechanism we have in mind concerns the composition effect of workers transitioning from non-employment during the recovery period (after a period of abnormally high unemployment duration). They will tend to have lower human capital and, for reasons detailed below, worse matches than already employed workers. This implies that the workers hired out of unemployment obtain lower wages and thereby put a drag on aggregate wage growth.

The second component of lower wage growth comes from the weaker bargaining position of the

newly employed workers. This mechanism yields what is sometimes refereed to as the "wage ladder" which follows from an assumption that individual wages depend both on current job offers and job offers accumulated over each worker's uninterrupted employment spell. Following a deep recession workers will tend to have shorter past employment spells than normal which further reduces the wage level and wage growth.

Let us perform a simple back-of-the-envelope calculation to hint at the quantitative relevance of variation in unemployment interacting with skill loss during unemployment and thereby affecting aggregate labor productivity. Indirect microdata estimates of skill loss when unemployed (relative to when employed) are roughly 1% per month (Schmieder, von Wachter and Bender, 2016) in a competitive labor market, or 2% per month if the surplus is equally shared between worker and employer. Let us consider an increase in unemployment of 4% for 3 years, as in the U.S. 2009-2011. This yields a decrease in aggregate human capital and thereby approximately aggregate labor productivity of $0.02 * 0.04 * 3 * 12 = 2.88\%$ (or 1.44% under the assumption of a competitive labor market) from these three years of deep recession. We argue that this amount is non-negligible, in particular when noting that labor force participation fell substantially during the period so that employment and thereby aggregate human capital was reduced more than what unemployment numbers imply. In addition, the unemployment rate remained substantially above average in 2012-2014 and employment rates have still not recovered to pre-crisis levels. Note also that any fall in aggregate productivity due to mismatch comes over and above these effects of human capital depreciation.

The specific exercise we perform is as follows. Using our model, we simulate the economy for 2007-2009 and match the time series for unemployment by filtering out the required exogenous TFP shocks. We then let the exogenous TFP process follow the usual pattern and document how much closer to the data for GDP, hours, labor productivity and real wages we get compared to a simple standard model without an endogenous component of TFP, i.e. without human capital dynamics and OJS which yields time-varying match-quality. More importantly, we study how much the subdued economic activity, in the particular the weak labor market, has reduced "potential output", i.e. the productive capacity of the economy. We do this by documenting the model-implied decrease in GDP, employment, labor productivity and wages after the exogenous part of the TFP has returned to its steady state. Our preliminary results indicate that both GDP and employment are substantially subdued due to the skill losses implied by the reduced economic activity during the Great Recession. In particular, 1 year after the exogenous driving force behind the Great Recession has fully dissipated, GDP is 2.3% lower and employment 1.6% lower than in the absence of the Great Recession.

We are well aware that many other factors, outside our model, also may have contributed to

subdued growth in the post-crisis period. This includes demand factors and long-term effects of the financial crisis not operating through the labor market , but also the fact that TFP trend growth appear to have started to decrease before the crisis (Fernald et al., 2017). We are merely quantifying one part of the reason for the slow and incomplete recovery after the crisis.

1.1 Previous literature

The idea that cyclical fluctuations, e.g. due to demand, affect future potential output and TFP is not new. A recent paper surveying the literature on hysteresis is Blanchard (2017). Switching instead to the time period of study, two existing papers explore how the Great Recession has affected TFP. In particular, both Anzoategui, Comin, Gertler and Martinez (2017) and Moran and Queralto (2018) quantify the degree to which decreased R&D has contributed to the slow recovery from the Great Recession. Here we instead explore the consequences of a more direct aspect of the cycle, the variation in employment and labor market dynamism in terms of re-allocation between jobs.

2 Model

2.1 Model overview

We perform our analysis in a business cycle model with a search and matching labor market allowing for heterogeneity of workers in terms of human capital and jobs in terms of match-specific productivity to capture the main mechanisms we are interested in. This requires allowing for i) modelling human capital dynamics and ii) employed workers to search for better jobs, i.e. on-the-job search. The model is identical to Walentin and Westermark (2018) who studied cost of business cycles and similar to Lise and Robin (2017), although the latter abstracted from workers' bargaining power and human capital dynamics.

Human capital of an employed worker is weakly increasing while for unemployed workers it is weakly decreasing, reflecting an assumption of learning on-the-job and skill loss during unemployment. The job ladder implies that during an employment spell a worker will gradually switch to better jobs. These mechanisms are theoretically well explored in the literature, but mainly in frameworks that abstract from aggregate volatility.[1] They will tend to induce additional persistence in productivity and wages and possibly increased volatility of the economy.

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[1]Learning on-the-job in settings without aggregate volatility is covered is Pissarides (1992) and more quantitatively in Ljungqvist and Sargent (1998). Huckfeldt models learning on-the-job in a setting with aggregate uncertainty. Chang et al. (2002) is the seminal paper analyzing learning on-the-job as an aggregate propagation mechanism. Lise and Robin (2017) model heterogeneity in match-specific productivity in the presence of aggregate uncertainty, in a way roughly similar to us. Moscarini and Postel-Vinay (2018) and Barlevy (2002) analyses the effects of the job ladder over the cycle.

We use the wage bargaining framework of Cahuc, Postel-Vinay and Robin (2006). This implies that a worker receives a value equal to his outside option plus a share β, reflecting his bargaining strength, of the value of the match above the outside option. When a worker is hired out of unemployment the outside option is the value of unemployment. If instead an employed worker receives a poaching offer from another firm, the outside option is the value of the second-best match. This wage setting framework was first implemented in a setting with aggregate uncertainty by Walentin and Westermark (2018).

Our model has only one fundamental source of aggregate fluctuations: exogenous TFP (identical to the exogenous component of labor productivity, as the we do not model any other inputs) shock. But note that measured TFP in the model will include both exogenous TFP as well as time-varying endogenous TFP that is driven by match-specific productivities and human capital levels, as well the sorting between these two.[2]

To fully capture the effects of heterogeneity we use global solution methods to solve the model. Solving the model is non-trivial as the value of posting a vacancy or accepting a job today depends on the labor market tightness tomorrow which, in turn, is a function of the next period distribution of workers and firms. As in Walentin and Westermark, we therefore use a Krusell and Smith (1998)-like algorithm to solve the model.

In terms of human capital dynamics, the model is in the tradition of Pissarides (1992) and Ljungqvist and Sargent (1998). As in these papers, we model general human capital as stemming from learning on-the-job and skill loss during unemployment. Worker human capital, denoted by x, follows a stochastic process and $\pi_{xe}(x, x')$ $(\pi_{xu}(x, x'))$ denote the Markov transition probability for the worker's human capital level while employed (unemployed). Firm match-specific productivity is denoted by y. Each firm employs (at most) one worker, and output from a match is $p(x, y, z) = xyz$ where z is an aggregate TFP shock with Markov transition probability $\pi(z, z')$.

Finally, we abstract from idiosyncratic household risk (by assuming risk-neutral workers) and from physical capital.

2.2 Timing

Let us start the detailed model description by providing an overview of the timing protocol. The sequence of events within a period are as follows. First, the aggregate productivity shock z and

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[2]Specifically, we have in mind the cyclical variation in the degree of assortative matching.

the idiosyncratic human capital shocks x are realized. Second, a fraction ν of workers die and are replaced by newborn unemployed workers with human capital at the lowest possible level, $\underline{x}$. Third, separations into unemployment occur. Then, firms post vacancies and workers search for jobs. Finally, new matches are formed, wages are set and production takes place.

2.3 Separations

The ability of recently separated workers to search for jobs within the period, makes it convenient to define match values and match surplus both before and after the search phase has occurred, i.e., at the separation stage and the matching stage. The surplus of a match at the separation stage is $S^s(x, y, z, \Gamma)$ where Γ denotes the endogenous aggregate state. Matches with $S^s(x, y, z, \Gamma) < 0$ are endogenously dissolved. In addition, a fraction δ of matches are exogenously destroyed every period.

The stock of unemployed workers after separations when the aggregate productivity evolves from z_{-1} to z is:

$$u^s(x, z) = \nu \mathbf{1}\{x = \underline{x}\} + (1 - \nu)\left[\sum_{x_{-1} \in X} u(x_{-1}, z_{-1}) \pi_{xu}(x_{-1}, x)\right. \tag{1}$$

$$\left. + \sum_{y \in Y} \sum_{x_{-1} \in X} (\mathbf{1}\{S^s(x, y, z, \Gamma) < 0\} + \delta \mathbf{1}\{S^s(x, y, z, \Gamma) \geq 0\}) h(x_{-1}, y, z_{-1}) \pi_{xe}(x_{-1}, x)\right]$$

where $\mathbf{1}\{\}$ is the indicator function, $u(h)$ is the distribution of unemployed (employed) workers at the end of a period, X is the set of human capital states and Y is the set of match-specific productivities. Here, the first term is the newborn workers and the remaining terms captures the evolution of the surviving workers.

The stock of matches of type (x, y) at this point is:

$$h^s(x, y, z) = (1 - \delta)(1 - \nu) \sum_{x_{-1} \in X} \mathbf{1}\{S^s(x, y, z, \Gamma) \geq 0\} h(x_{-1}, y, z_{-1}) \pi_{xe}(x_{-1}, x). \tag{2}$$

2.4 Search and matching

An employed worker exerts search effort s_1. The search effort of unemployed workers is normalized to unity. Accordingly, the aggregate amount of search effort is:

$$L \equiv \sum_{x \in X} u^s(x, z) + s_1 \sum_{x \in X} \sum_{y \in Y} h^s(x, y, z). \tag{3}$$

Vacancy posting costs are linear and each vacancy posted incurs a cost of c_0. The free entry

condition for vacancy creation therefore implies:

$$c_0 = qJ(z, \Gamma).\tag{4}$$

where q is the probability of a firm meeting a worker and J is the expected value of a new match for a firm, as defined below.

We assume the following Cobb-Douglas meeting function:

$$M \equiv \min\left\{\alpha L^\omega V^{1-\omega}, L, V\right\}\tag{5}$$

where V is the number of vacancies posted. The probability of a firm meeting a worker (assuming an interior solution) is:

$$q = \frac{M}{V} = \alpha\theta^{-\omega},$$

where $\theta \equiv \frac{V}{L}$ is labor market tightness. Together with the matching function (5), this implies that equilibrium vacancy postings are determined by:

$$V = L\left(\frac{\alpha J(z, \Gamma)}{c_0}\right)^{\frac{1}{\omega}}.\tag{6}$$

We can then write labor market tightness as a function of z and Γ:

$$\theta(z, \Gamma) = \left(\frac{\alpha J(z, \Gamma)}{c_0}\right)^{\frac{1}{\omega}}.\tag{7}$$

Finally, the probability that an unemployed worker meets a firm (the job meeting rate) is, assuming an interior solution:

$$f(z, \Gamma) = \frac{M}{L} = \alpha\theta(z, \Gamma)^{1-\omega}.\tag{8}$$

2.5 Values

A worker who is unemployed during the production phase receives a flow payoff of $b(x, z)$ representing unemployment insurance, utility of leisure and value of home production. The value of unemployment at the matching stage is:

$$B(x, z, \Gamma) = b(x, z)\tag{9}$$
$$+ \frac{1-\nu}{1+r}\sum_{x' \in X}\sum_{z' \in Z}[\sum_{y' \in Y} f(z', \Gamma')\left[B(x', z', \Gamma') + \beta\max\left\{P(x', y', z', \Gamma') - B(x', z', \Gamma'), 0\right\}\right]g(y')$$
$$+ (1 - f(z', \Gamma'))B(x', z', \Gamma')] \times \pi_{xu}(x, x')\pi(z, z'),$$

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where r is the discount rate, Z is the set of aggregate productivity states, P the value of a match and $g(y)$ is the probability density function (pdf) of the productivity of newly created matches. Thus, B is the flow payoff b plus the job meeting rate $f(z', \Gamma')$ times the discounted value of a job tomorrow plus $(1 - f(z', \Gamma'))$ times the discounted value of being unemployed tomorrow. The max operator ensures that only matches with positive surplus are formed. Note that while a worker is unemployed his human capital (weakly) decreases from x to x' with probability $\pi_{xu}(x, x')$.

The match value at the matching stage, using that the job meeting rate for employed workers is $s_1 f(z', \Gamma')$, can be written as follows:

$$P(x, y, z, \Gamma) = p(x, y, z) + \frac{1 - \nu}{1 + r} \sum_{x' \in X} \sum_{z' \in Z} [(1 - (1 - \delta) p_{P>B}^o) B^s (x', z', \Gamma') + (1 - \delta) p_{P>B}^o$$

$$\times \{ \sum_{\tilde{y}' \in Y} s_1 f(z', \Gamma') \{ P(x', y, z', \Gamma') + \beta \max [P(x', \tilde{y}', z', \Gamma') - P(x', y, z', \Gamma'), 0] \} g(\tilde{y}') \quad (10)$$

$$+ (1 - s_1 f(z', \Gamma')) P(x', y, z', \Gamma') \}] \pi_{xe}(x, x') \pi(z, z')$$

where $\tilde{y}'$ denotes the match quality of the poaching firm and where the indicator for non-separation is:

$$p_{P \geq B}^o = \mathbf{1} \{ P^s (x', y, z', \Gamma') \geq B^s (x', z', \Gamma') \}.$$

Here, B^s is the value when unemployed and P^s is the value of the match at the separation stage, respectively. The first term in (10) is the flow output, the second term the value when the match separates tomorrow, the third term the value when receiving a poaching offer tomorrow and the last term the value when not receiving a poaching offer tomorrow. Also note that, regardless of what happens tomorrow, human capital while employed today increases from x to x' with probability $\pi_{xe}(x, x')$.

We also need to compute the values at the separation stage. The value for an unemployed worker at the separation stage is:

$$B^s (x, z, \Gamma) = (1 - f(z, \Gamma)) B(x, z, \Gamma) \quad (11)$$

$$+ \sum_{\tilde{y} \in Y} f(z, \Gamma) [B(x, z, \Gamma) + \beta \max \{ P(x, \tilde{y}, z, \Gamma) - B(x, z, \Gamma), 0 \}] g(\tilde{y}).$$

The corresponding match value at the separation stage is:

$$P^s (x, y, z, \Gamma) = (1 - s_1 f(z, \Gamma)) P(x, y, z, \Gamma) \quad (12)$$

$$+ \sum_{\tilde{y} \in Y} s_1 f(z, \Gamma) [P(x, y, z, \Gamma) + \beta \max \{ P(x, \tilde{y}, z, \Gamma) - P(x, y, z, \Gamma), 0 \}] g(\tilde{y}).$$

Then, we can simply define the surplus of a match at the matching stage as:

$$S\left(x,y,z,\Gamma\right) = P\left(x,y,z,\Gamma\right) - B\left(x,z,\Gamma\right) \tag{13}$$

and the surplus of a match at the separation stage as:

$$S^s\left(x,y,z,\Gamma\right) = P^s\left(x,y,z,\Gamma\right) - B^s\left(x,z,\Gamma\right). \tag{14}$$

Recalling that workers receive a value corresponding to their outside option plus a share β of the surplus of the match, the expected value of a new match for a firm is:

$$
\begin{aligned}
J\left(z,\Gamma\right) = & \frac{1}{L}\sum_{x\in X}\sum_{y\in Y}u^s\left(x,z\right)\max\left\{\left(1-\beta\right)S\left(x,y,z,\Gamma\right),0\right\}g\left(y\right) \\
& +\frac{s_1}{L}\sum_{x\in X}\sum_{y\in Y}\sum_{\tilde{y}\in Y}h^s\left(x,\tilde{y},z\right)\max\left\{\left(1-\beta\right)\left(S\left(x,y,z,\Gamma\right)-S\left(x,\tilde{y},z,\Gamma\right)\right),0\right\}g\left(y\right).
\end{aligned}
\tag{15}
$$

Note that the match-specific productivity, y, is observed when the firm meets a worker after the vacancy has been posted.[3] The first term in (15) refers to expected surplus from recruiting out of the pool of unemployed (u^s), and the second term refers to expected surplus from recruiting from employed workers (h^s). As can be seen from (15), the distribution of unemployed workers across human capital and the distribution of matches over human capital and match-specific productivity is the endogenous aggregate state. Hence, Γ can be written as a function of L and the two terms within the summations in (15)

Let us here mention a computational aspect of the model. Solving the model is non-trivial because current values (9) and (10) depend on the probability of receiving a job offer the next period. This, in turn, depends on the next period's labor market tightness. A key determinant for the next period's tightness is the expected value of a new match to a firm in the next period, i.e., $J\left(z',\Gamma'\right)$. This depends on the next period distribution of workers and firms. Fortunately, as argued in the previous paragraph, three moments fully capture the implications of this large-dimensional object. We then use a Krusell and Smith (1998)-like algorithm to let these three moments summarize and predict the labor market tightness, thereby enabling us to solve the model.

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[3]This assumption substantially simplifies the computation of the equilibrium.

2.6 Distributional dynamics

For a new match to be formed, two conditions are required: the two parties must meet according to the meeting function (5) and the match must be an improvement over the status quo (the current match or unemployment). The unemployment distribution after matching accordingly is:

$$u(x,z) = u^s(x,z)\left(1 - \frac{M}{L}\sum_{y \in Y} \mathbf{1}\{S(x,y,z,\Gamma) \geq 0\} g(y)\right). \tag{16}$$

The corresponding expression for the distribution of matches is:

$$
\begin{aligned}
h(x,y,z) = \quad & h^s(x,y,z) + \underbrace{u^s(x,z)\frac{M}{L}\mathbf{1}\{S(x,y,z,\Gamma) \geq 0\} g(y)}_{\text{mass hired from unemployment}} \\
& \underbrace{- h^s(x,y,z) s_1 \frac{M}{L}\sum_{\tilde{y} \in Y} \mathbf{1}\{S(x,\tilde{y},z,\Gamma) > S(x,y,z,\Gamma)\} g(\tilde{y})}_{\text{mass lost to more productive matches}} \\
& \underbrace{+ s_1 \frac{M}{L}\sum_{\tilde{y} \in Y} h^s(x,\tilde{y},z)\mathbf{1}\{S(x,y,z,\Gamma) > S(x,\tilde{y},z,\Gamma)\} g(y)}_{\text{mass poached from less productive matches}}.
\end{aligned} \tag{17}
$$

2.7 Wage determination and worker values

Let $W(w,x,y,z,\Gamma)$ denote the present value to a worker with human capital x in a match with productivity y, wage w and aggregate productivity z. These worker values are determined according to the bargaining protocol in CPVR and are detailed as follows. Denote the renegotiated wage by w'. Workers hired out of unemployment receive the wage w' such that their value is equal to the value of unemployment plus a share β of the match surplus:

$$W(w',x,y,z,\Gamma) = B(x,z,\Gamma) + \beta S(x,y,z,\Gamma). \tag{18}$$

For employed workers who have received a poaching offer, the bargaining protocol implies that these workers receive a present value $W(w',x,y,z,\Gamma)$ equal to the value of the second-best match that they have encountered during a spell of continuous employment plus a share β of the difference in surplus between the best and second-best match. Formally, if a worker of type x employed at a firm of type y meets a firm of type $\tilde{y}$ then, if $S(x,y,z,\Gamma) < S(x,\tilde{y},z,\Gamma)$, the worker switches to the new firm and gets the wage w' satisfying

$$W(w',x,\tilde{y},z,\Gamma) = P(x,y,z,\Gamma) + \beta[S(x,\tilde{y},z,\Gamma) - S(x,y,z,\Gamma)]. \tag{19}$$

If, instead, $S\left(x,y,z,\Gamma\right) \geq S\left(x,\tilde{y},z,\Gamma\right)$, the worker remains in his current match and gets a wage w' that satisfies:

$$W\left(w',x,y,z,\Gamma\right) = \max\left\{P\left(x,\tilde{y},z,\Gamma\right) + \beta\left[S\left(x,y,z,\Gamma\right) - S\left(x,\tilde{y},z,\Gamma\right)\right], W\left(w,x,y,z,\Gamma\right)\right\}. \quad (20)$$

Note that, in case the value at the current wage is higher than the one implied by the outside option, the wage is unchanged.

Wages for workers who do not receive poaching offers can also be rebargained, as aggregate or idiosyncratic shocks might affect the various values. First, if the wage is such that it implies a worker value that is larger than the match value, then the match would break down unless there is renegotiation. Hence, the wage is then set so that $W\left(w',x,y,z,\Gamma\right) = P\left(x,y,z,\Gamma\right)$. Second, if the wage is such that the worker value is lower than $B\left(x,z,\Gamma\right) + \beta S\left(x,y,z,\Gamma\right)$, the worker can ask for a renegotiation with unemployment as the outside option. Hence, the wage is then set so that $W\left(w',x,y,z,\Gamma\right) = B\left(x,z,\Gamma\right) + \beta S\left(x,y,z,\Gamma\right)$. Finally, the current wage w is unchanged when:

$$B\left(x,z,\Gamma\right) + \beta S\left(x,y,z,\Gamma\right) \leqslant W\left(w,x,y,z,\Gamma\right) \leqslant P\left(x,y,z,\Gamma\right). \quad (21)$$

To solve for wages, we compute the value for a worker earning w today, given that future values are (partially) determined by (18)-(21). An employed worker earning the wage w in the current period faces four possibilities in the next period: i) staying employed and not meeting any new firm, ii) staying employed and receiving a successful poaching offer and switching jobs, iii) staying employed and receiving an unsuccessful poaching offer (and staying in the old job) and iv) separating. Note that, if the worker becomes separated in the next period he still has a chance to find a new job within the period. Imposing an interior solution for M, $M = \alpha L^{\omega}V^{1-\omega}$ and using the definition of q, the probability of meeting a new firm for an employed worker is $s_1 f\left(z',\Gamma'\right)$. Then, given the wage, w, the worker value (at the matching stage) is:

$$
\begin{aligned}
W\left(w,x,y,z,\Gamma\right) = w + \frac{1-\nu}{1+r}\sum_{x'\in X}\sum_{z'\in Z} & \left[\left(1-s'\right)\left\{\left(1-s_1 f\left(z',\Gamma'\right)\right)W'_{np}\right.\right. \qquad (22)\\
& \left. + s_1 f\left(z',\Gamma'\right)\sum_{\tilde{y}\in Y}\left(p^o_{\tilde{y}>y}W'_{p,\tilde{y}>y} + \left(1-p^o_{\tilde{y}>y}\right)W'_{p,\tilde{y}\leq y}\right)g\left(\tilde{y}\right)\right\}\\
& \left. + s'\left(B\left(x',z',\Gamma'\right) + f\left(z',\Gamma'\right)\sum_{y'\in Y}\beta S\left(x',y',z',\Gamma'\right)g\left(y'\right)\right)\right]\pi_{xe}\left(x,x'\right)\pi\left(z,z'\right),
\end{aligned}
$$

where

$$s' = \left(\mathbf{1}\left\{S\left(x',y,z'\right) < 0\right\} + \delta\mathbf{1}\left\{S\left(x',y,z',\Gamma'\right) \geq 0\right\}\right)$$

$$W'_{np} = \min\left\{P\left(x',y,z',\Gamma'\right), \max\left\{W\left(w,x',y,z',\Gamma'\right), B\left(x',z',\Gamma'\right) + \beta S\left(x',y,z',\Gamma'\right)\right\}\right\}$$

$$p^o_{\tilde{y}>y} = \mathbf{1}\left\{S\left(x',\tilde{y},z',\Gamma'\right) > S\left(x',y,z',\Gamma'\right)\right\}$$

$$W'_{p,\tilde{y}>y} = P\left(x',y,z',\Gamma'\right) + \beta\left[S\left(x',\tilde{y},z',\Gamma'\right) - S\left(x',y,z',\Gamma'\right)\right]$$

$$W'_{p,\tilde{y}\leq y} = \max\left\{P\left(x',\tilde{y},z',\Gamma'\right) + \beta\left[S\left(x',y,z',\Gamma'\right) - S\left(x',\tilde{y},z',\Gamma'\right)\right], W\left(w,x',y,z',\Gamma'\right)\right\},$$

where s' denotes separations, W'_{np} the value when not receiving a poaching offer, $p^o_{\tilde{y}>y}$ a successful poaching offer, $W'_{p,\tilde{y}>y}$ the value of a successful poaching offer and $W'_{p,\tilde{y}\leq y}$ the value of an unsuccessful poaching offer.

2.8 Wage distribution

When determining the wage distribution, it follows from the description of the wage setting above that the current wage of the worker is a state variable. The distribution of matches over w, x and y after separations is:

$$h^{s,w}\left(w,x,y,z\right) = \left(1-\delta\right)\left(1-\nu\right)\sum_{x_{-1}\in X}\mathbf{1}\left\{S^s\left(x,y,z,\Gamma\right)\geq 0\right\}h^w\left(w,x_{-1},y,z_{-1}\right)\pi_{xe}\left(x_{-1},x\right). \quad (23)$$

Analogously to (17) in section 2.6, we define $h^w\left(w,x,y,z\right)$, i.e., the distribution after matching and wage rebargaining; see Appendix A.1.

3 Calibration

3.1 Distributions and shock processes

The log of the exogenous part of TFP, z, follows an AR(1) process approximated by a Markov chain. The log of match productivity, $g\left(y\right)$, is normally distributed and its mean value is normalized to 0.5. The number of gridpoints for x, y and z are 10, 8 and 7, respectively.[4] The wage grid contains 15 points and is chosen separately for each parameter vector so as to only cover the relevant wage interval.[5] In constructing the grid for human capital, x, we, as e.g., Jarosch (2015), follow Ljungqvist and Sargent (1998, 2008) in using an equal-spaced grid and in setting the ratio between the maximum and

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[4]For z, we use Tauchen and Hussey's (1991) discretization of AR(1) processes with optimal weights from Flodén (2008). This algorithm has been shown by Flodén (2008) to also be accurate for processes with high persistence.

[5]The coarseness of the wage grid is less restrictive than it seems, as we map each "off-the-grid" wage to the two nearest grid points using the inverse of the distance to the grid point as weight. Furthermore, the wage grid has no impact on the allocations in the model.

minimum value of x to 2. The structure of the transition matrices $\pi_{xe}(x, x')$ and $\pi_{xu}(x, x')$ for human capital also closely follows Ljungqvist and Sargent. Abstracting from the bounds, the probability of an employed worker to increase his human capital by one gridpoint is x_{up} and the probability for an unemployed worker to decrease his human capital by one gridpoint is x_{dn}. With the reciprocal probabilities, the human capital of a worker is unchanged.

3.2 Calibration approach

The frequency of the model is monthly. We calibrate the model based on U.S. data. Parameters whose values are well established in the literature or can be set based on model-independent empirical evidence are set outside the model. Table 1 documents these parameter values and their sources.

Table 1: Parameters set outside the model

	Explanation	Value	Source
ω	Matching function elasticity	0.5	Pissarides (2009)
β	Bargaining power of workers	0.5	**Literature consensus**
δ	Exogenous match separation rate	0.018	Fujita-Ramey (2009)
c_0	Vacancy posting cost	0.06375	Fujita-Ramey (2012)
ν	Retirement rate	$1/(40 * 12)$	40-year work-life
ρ	TFP shock persistence	0.960	Hagedorn-Manovskii
r	Interest rate	$1.05^{1/12} - 1$	Annual r of 5%

The meeting function elasticity, ω, and the bargaining power of workers, β, are set in line with the convention in the literature. The exogenous match separation rate, δ, is set equal to the ratio of non-layoffs in JOLTS 2001-2011 (0.598) multiplied by the mean E2U transition rate reported by Fujita and Ramey (2009), adjusted for workers finding a new job the same month as they lost the old job.[6] We set the vacancy posting cost c_0 along the lines for Fujita and Ramey (2012) who refer to evidence that vacancy costs are 6.7 hours per week posted. We set the retirement (or death) rate to match an average work-life of 40 years, as e.g. Huckfeldt (2016). To compute the persistence of the AR process for TFP, we follow along the lines of Hagedorn and Manovskii (2008). Specifically, we simulate a monthly Markov chain to match a quarterly autocorrelation of (HP-filtered) log labor productivity of 0.765. Finally, we set r to yield an annualized interest rate of 5% as in LR.

The remaining parameters of our model are calibrated jointly to match key moments. Flow payoff from unemployment is $b(x, z) = b_0 + b_1 x$, so that b_0 represents the component of the unemployment payoff that is equal for all workers, while b_1 captures the dependence on human capital. Table 2 documents the 8 calibrated parameters and the 8 moments matched, including the main identifying

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[6]The latter implies that the separation rate exceeds the E2U rate by a factor of 1/(1-job finding rate). By using Fujita and Ramey's number for E2U transitions, we control for the fact that empirically, but not in our model, workers flow in and out of the labor force.

Table 2: Parameters obtained by moment-matching

Parameter	Explanation	Value	Main identifying moment
α	Matching function productivity	0.321	U2E transition rate, mean
s_1	Relative search intensity of employed	0.136	J2J transition rate, mean
x_{up}	Human capital gain, probability	0.063	Return to experience
b_0	Unemployment payoff, intercept	0.022	Unemployment, std.dev.
b_1	Unemployment payoff, coefficient	1.366	Mueller coefficient
σ_y	Match-specific productivity dispersion	0.161	E2U transition rate, mean
ρ_y	Match-specific productivity persistence	0.510	Wage disp: Mean-min ratio
$100\sigma_z$	TFP shock std.dev.	0.533	GDP, std.dev.

moment for each parameter. We minimize the squared percentage deviation between model and data moments. Let us now motivate the choice of moments. Regarding identification, the model parameters are jointly estimated, but some moments are more informative about certain parameters. The mean transition rate from unemployment to employment is informative about the matching function productivity α. The job-to-job transition rate is informative about the relative search intensity of employed workers s_1. Return to experience, measured as the average percentage wage increase while employed, is informative about on-the-job accumulation of human capital, x_{up}.[7] Unemployment volatility is informative about the unemployment payoff parameter, b_0, while the cyclicality of previous wages in the unemployment pool as measured by the Mueller coefficient is informative about b_1. The mean E2U transition rate is informative about the volatility of match-specific productivity shocks, σ_y, while wage dispersion is informative about the persistence of match-specific productivity, ρ_y. Finally, the volatility of GDP and unemployment are both informative about the standard deviation of the aggregate productivity process, σ_z.

Let us comment on the cross-sectional data we use. The relevant measure of wage dispersion for our model is "residual" wage dispersion, i.e. controlling for heterogeneity not present in the model, such as education, sex, race etc. We take the mean-min ratio (capturing the minimum by the 10th wage percentile) from Hornstein, Krusell and Violante (2007) as our measure of wage dispersion. We use their preferred measure of 1.50, which is an average of their ratios from census, OES and PSID data. Similarly to Kehoe et al. (2015) we use estimates from Buchinsky et al. (2010) to obtain the

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[7] As in Jarosch (2015), we impose a relationship between x_{up} and x_{dn} such that the number of increases in human capital roughly equals the number of decreases to minimize bunching at end-points of the human capital grid X. In particular, letting u^{tot} denote the (implicitly, through the mean values of E2U and U2E) targeted value of unemployment, we impose $(1-\nu)\,x_{up}\,(1-u^{tot})\,\Delta x = (1-\nu)\,x_{dn}u^{tot}\Delta x + \nu\,(\bar{x}-\underline{x})$ where Δx is the distance between two gridpoints and $\bar{x}$ represents average human capital for dying workers. For computational reasons, we set $\bar{x}$ to the midpoint of the grid. Furthermore $\underline{x}$ is the lower bound of the grid, representing the human capital of newly born workers. This implies $x_{dn} = \left(x_{up} - \frac{\nu}{1-\nu}\frac{[\bar{x}-\underline{x}]}{(1-u^{tot})\Delta x}\right)\frac{1-u^{tot}}{u^{tot}}$. There will still be some upward drift, and thereby upper end-point bunching, in the human capital distribution if an above-proportional fraction of the unemployed are at the lower bound of the human capital grid, unless this is offset by the analogous force of above-proportional fraction of employed workers at the upper bound.

Table 3: Data moments and matched model moments

Moment	Data source	Target value (data)	Model value
U2E transition rate, mean	Fujita-Ramey (2009)	0.340	0.283
E2U transition rate, mean	Fujita-Ramey (2009)	0.020	0.018
J2J transition rate, mean	Moscarini-Thompson	0.0320	0.039
Unemployment, std.dev.	BLS 1980-2010	0.107	0.097
GDP, std.dev.	BEA 1980-2010	0.0136	0.015
Wage disp: Mean-min ratio	Hornstein et al.	1.50	1.71
Mueller coefficient of U on wage	Mueller (2017)	0.75	0.75
Return to experience	Buchinsky et al.	0.0548	0.040

Notes: U2E, E2U and J2J transition rates are at a monthly frequency. Unemployment is a quarterly mean of a monthly series. This variable, as well as GDP, labor productivity and aggregate wages, have been logged and HP-filtered with $\lambda = 1,600$, both in the data and the model.

"return to experience". Specifically, from Buchinsky's estimated coefficients we obtain the marginal return to experience of a worker in his third year of employment. We then match that to the wage increase of workers in the model who works for three years for the same employer. We can thereby keep the match-specific productivity fixed and obtain a clean measure of the effect of human capital on wages. We model individual human capital on a grid, which implies that it is bounded within an interval. Accordingly, differently from all other workers, a worker at the lower end of this interval can not suffer from further skill loss (human capital depreciation), and vice versa for employed workers at the upper end of the interval. This implies that the distribution of human capital of unemployed workers, including its cyclical variation, matter for how the aggregate human capital is affected by unemployment. We therefore make sure that our model lines up with the data regarding the cyclical composition of the unemployment pool. In particular, in our calibration we match the cyclical variation in the previous wages of unemployed workers as documented by Mueller (2017) using CPS data for the U.S. Mueller runs the following regression that relates previous wages of unemployed workers, w_t^u, and wages for all workers, w_t, to the unemployment rate, U_t: $\log(w_t^u) - \log(w_t) = \alpha + \beta U_t + \varepsilon_t$. We run the same regression on simulated output from our model and target $\hat{\beta} = 0.75$ as reported by Mueller (2017) for the residual wage, i.e. controlling for a number of fixed effects, like gender, industry, occupation etc.[8]

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[8]We also follow Mueller in that we observe wages, w_t^u, and w_t, at an annual frequency and detrend them using a HP-filter with $\lambda = 100$.

4 Results

4.1 Targeted moments and the parameter estimates

The moment-matching exercise can be evaluated by comparing the last two columns in Table 3. The model is able to fit most of these moments well, with less than 20 percent deviation for all but two moments; the average J2J transition rate and the return to experience.

The above moment-matching exercise determines the 8 parameters in Table 2. The value for s_1 in Table 2 indicates that unemployed workers meet prospective employers roughly eight times as often as employed workers. We follow LR and report the replacement ratio for unemployed workers as a fraction of the output of the best possible match. The values of b_0 and b_1 imply that this ratio is 1.06, averaged over the human capital values, and that the unemployment payoff is very close to proportional to human capital.[9] Our estimate of ρ_y indicates that match-specific shocks are very transitory.

Given their centrality for our mechanism, we report and comment in more detail on our estimates of the parameters determining the human capital dynamics. The estimated Markov transition probability ($x_{up} = 0.063$) imply that the expected monthly human capital increase for an employed worker is 0.232 percent, while the expected decrease when unemployed is 1.23 percent (for $x_{dn} = 0.897$).[10]

The human capital dynamics can be compared to estimates in models broadly similar to ours.[11] Huckfeldt (2016) reports a 0.330 percent expected monthly human capital increase for workers in skill-intensive jobs (0.220 percent in skill-neutral jobs). For unemployed workers Huckfeldt obtains a gradual human capital decrease of 1.13 percent per month. Jarosch (2015) reports only the monthly human capital Markov transitions probabilities: 0.0141 for employed and 0.131 for unemployed. In Jarosch (2015), for an employed worker with the mid-point of human capital, this implies an expected increase of 0.134 percent, and for the unemployed worker with the mid-point of human capital, it implies a 1.25 percent decrease. To sum up this comparison to the literature, our human capital accumulation

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[9]Note that employment implies other benefits in addition to the wage (notably human capital accumulation), which is why a pecuniary replacement rate above unity is possible.

[10]This value takes into account the distribution of employed and unemployed workers across the human capital grid, including the effects of the bounds of the human capital grid.

[11]First, there is an older empirical literature that attributes all wage loss when re-employed after an unemployment spell to human capital loss and furthermore assumes that the wage equals marginal product of labor. This is not consistent with our model so we can not use that literature for calibration or straight comparison. Second, some papers look at the effect on wages of an additional month of unemployment. The estimates in Neal (1995) imply that an additional month of unemployment reduces the re-employment wage by 1.5%, which, under the assumption that the wage equals marginal product of labor, is very much in line with our results. Recent results by Schmieder et al. (2016) shows that re-employment wages decrease by 0.8% per (additional) month unemployed. This is somewhat lower than our result, but reasonably well in line if one thinks that there is some surplus sharing so that wages decrease less than human capital for an additional month of unemployment.

for employed workers is in between the estimates of Huckfeldt (2016) and Jarosch (2015), while for unemployed workers our value is about as large as their estimates.

4.2 Evidence from the Great Recession

In this section we document both the initial increase in unemployment 2007-2009 and the slow recovery from the Great Recession in term of the variables of interest. For our quantitative exercise me take as a key input the dramatic increase of unemployment of roughly 5% 2007-2009 (from 4.6% in January 2007 to 10.3% in December 2009) and the very slow unemployment recovery thereafter. The fact that we abstract from the fall in labor force participation that occured during the Great Recession is conservative in that it implies that we understate the negative of effects on the productive capacity of the economy.

4.3 Model implications for slow recoveries

Our main object of interest is the medium run consequences of the temporary increase in unemployment that the Great Recession implied. The exercise we perform is as follows: Starting from a simulation where the exogenous part of TFP has been at its average value for many years, we simulate the Great Recession by setting TFP to the lowest value on its grid, so that unemployment increase by roughly 5%, as in the Great Recession. We then let TFP gradually recover over 4 years (say fully recovered by the end of 2013) and document the difference between initial pre-crisis values of macroeconomic variables and their values one year after TFP-normalization is complete in Table X. Figure 1 and 2 document the model-implied path of all variables of interest. As can be seen from both the figures and Table 4 the medium run effects of the Great Recession are substantial. The recession leads to a collapse in job creation and the increased unemployment reduces the human capital of the unemployed workers, which, in turn, creates persistently low job creation and lowers GDP and employment.

Table 4: Change in value of variable from before the Great Recession to 1 year after the exogenous TFP shock has fully dissipated.

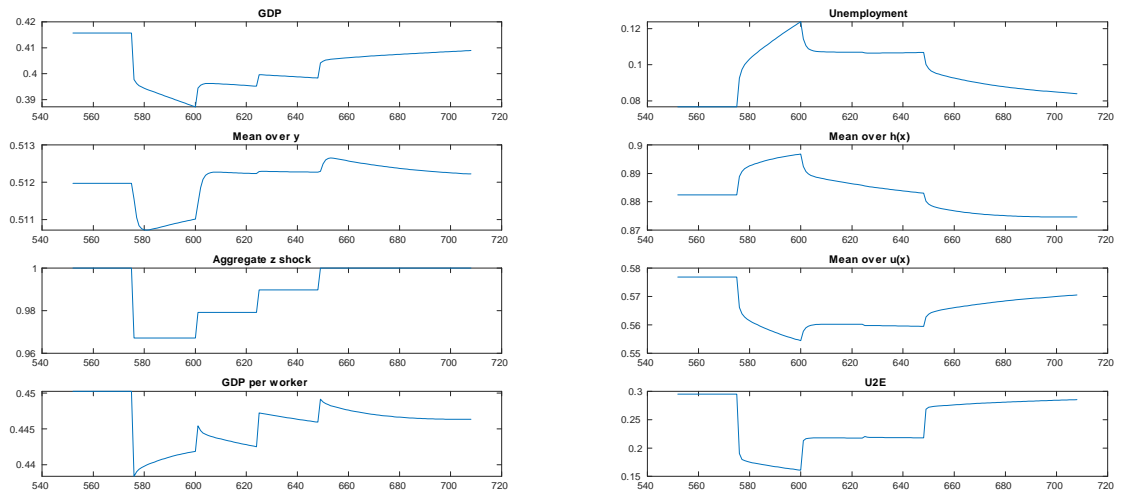|	Change (in percent)
GDP	-2.30
GDP/worker	-0.58
Unemployment (percentage points)	+1.59
Human capital of employed workers, $E\left(x \times h\left(\cdot\right)\right)$	-0.63
Human capital of unemployed workers, $E\left(x \times u\left(\cdot\right)\right)$	-1.87
Average wage	-0.94

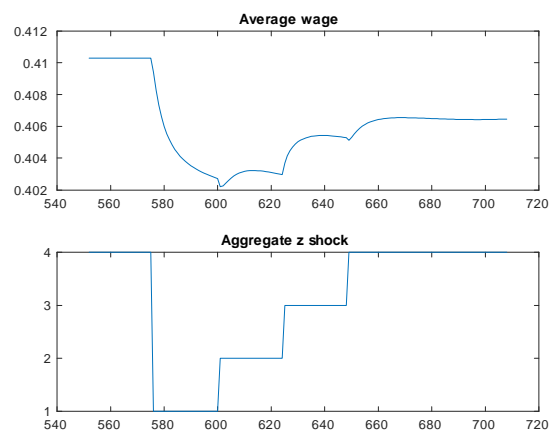Figure 1: Implications of the Great Recession.

Figure 2: Wage implications of the Great Recession.

5   Conclusions

TBW

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A Appendix

A.1 Employment transitions

When accounting for the wage distribution, the employment transition follows:

$$h^w\left(w^*,x,y,z\right) =$$

$$h^{s,w}\left(w^*,x,y,z\right) - \underbrace{h^{s,w}\left(w^*,x,y,z\right)s_1\frac{M}{L}\sum_{\tilde{y}\in Y}p^o_{\tilde{y}>y}g\left(\tilde{y}\right)}_{\text{mass lost to more productive matches}}$$

$$-\underbrace{h^{s,w}\left(w^*,x,y,z\right)s_1\frac{M}{L}\sum_{\tilde{y}\in Y}\mathbf{1}\left\{P\beta\left(x,\tilde{y},y,z,\Gamma\right)>W\left(w^*,x,y,z,\Gamma\right)\right\}\left(1-p^o_{\tilde{y}>y}\right)g\left(\tilde{y}\right)}_{\text{mass lost to higher wage offers from less productive matches}}$$

$$+\underbrace{s_1\frac{M}{L}\sum_{\tilde{y}\in Y}\sum_{\tilde{w}\in W^{grid}}h^{s,w}\left(\tilde{w},x,y,z\right)\mathbf{1}\left\{w\left(\tilde{w},x,y,z,\Gamma\right)=w^*\right\}\left(1-p^o_{\tilde{y}>y}\right)g\left(\tilde{y}\right)}_{\text{mass gained from increased wage due to offers from less productive matches}}$$

$$+\underbrace{s_1\frac{M}{L}g\left(y\right)\sum_{\tilde{y}\in Y}h^s\left(x,\tilde{y}\right)\mathbf{1}\left\{W\left(w^*,x,y,z,\Gamma\right)=P\left(x,\tilde{y},z,\Gamma\right)+\beta\left[S\left(x,y,z,\Gamma\right)-S\left(x,\tilde{y},z,\Gamma\right)\right]\right\}p^o_{y>\tilde{y}}}_{\text{mass poached from less productive matches}}$$

$$-\underbrace{h^{s,w}\left(w^*,x,y,z\right)\mathbf{1}\left\{W\left(w^*,x,y,z,\Gamma\right)\notin BS\left(x,y,z,\Gamma\right)\right\}}_{\text{mass lost due to being outside bargaining set}} \tag{24}$$

$$+\underbrace{\sum_{\tilde{w}\in W^{grid}}h^{s,w}\left(\tilde{w},x,y,z\right)\mathbf{1}\left\{w\left(\tilde{w},x,y,z,\Gamma\right)=w^*\right\}\mathbf{1}\left\{W\left(\tilde{w},x,y,z,\Gamma\right)\notin BS\left(x,y,z,\Gamma\right)\right\}}_{\text{mass gained from other wages being outside bargaining set}}$$

$$+\underbrace{\frac{M}{L}u^s\left(x\right)g\left(y\right)S_{xyz}\mathbf{1}\left\{W\left(w^*,x,y,z,\Gamma\right)=B\left(x,z,\Gamma\right)+\beta S\left(x,y,z,\Gamma\right)\right\}}_{\text{mass hired from unemployment}}$$

where W^{grid} is the wage grid and

$$p^o_{\tilde{y}>y} \equiv \mathbf{1}\left\{P\left(x,\tilde{y},z,\Gamma\right)>P\left(x,y,z,\Gamma\right)\right\}$$

$$P\beta\left(x,\tilde{y},y,z,\Gamma\right) = P\left(x,\tilde{y},z,\Gamma\right)+\beta\left[S\left(x,y,z,\Gamma\right)-S\left(x,\tilde{y},z,\Gamma\right)\right]$$

$$p^o_{y>\tilde{y}} \equiv \mathbf{1}\left\{P\left(x,y,z,\Gamma\right)>P\left(x,\tilde{y},z,\Gamma\right)\right\}$$

$$BS\left(x,y,z,\Gamma\right) = \left[B\left(x,z,\Gamma\right)+\beta S\left(x,y,z,\Gamma\right),P\left(x,y,z,\Gamma\right)\right]$$

$$S_{xyz} \equiv \mathbf{1}\left\{S\left(x,y,z,\Gamma\right)\geq 0\right\}$$