Essays on the Macroeconomic Consequences of Microeconomic Frictions

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Introduction

This thesis explores the macroeconomic implications of micro-level frictions. In chapter 2 we explore whether persistent productivity differences at the micro-level should be understood as a result of a friction in technology choice, and quantifies the efficiency losses in the economy. In chapter 3 we empirically assess through which channels - factor adjustment costs, price rigidities, or financial frictions - do uncertainty shocks affect the aggregate economy. Finally, in chapter 4 we quantify trends in labor income risk and study its implications for welfare and inequality in the context of a model where workers face search frictions to find jobs. The remainder paragraphs from the introduction preview the contribution from each chapter in some more detail.

Chapter 2. In this chapter we use plant and firm-level data from Chile, Colombia, Germany and Indonesia to decompose labor and capital productivity into a persistent and a transitory component. We find that most of the dispersion in factor productivities is explained by their persistent component, and related to highly persistent differences in the capital-labor ratio.

We show that our empirical findings cannot be explained by factor adjustment frictions, while they are in line with the empirical implications from frictional technology choice. A setup where firms operate a technology which they adjust only occasionally, and in between adjustments, production technology - capital intensity - is Leontief.

We use this framework to quantify the aggregate productivity losses from a friction in technology choice. The efficiency losses are determined by the elasticity of substitution between production factors and the cross-sectional variance of capital intensity. Despite the large heterogeneity in micro-level capital intensity, the efficiency losses are low compared to the literature. The estimated elasticity of substitution plays an important role for our results. In our setting, aggregate capital intensity does not fully accommodate to price movements due to a friction in technology choice. Once we account for this underreaction, we obtain an above one elasticity of substitution, which reduces substantially the resulting efficiency losses.

Chapter 3. We show that the response of aggregate job flows from uncertainty shocks depends whether establishments face factor adjustment frictions, price rigidities, or financial frictions.

Making use of these implications, we estimate the effect of uncertainty shocks on industry-level job flows in the United States. An unexpected increase in uncertainty implies more jobs destroyed and less jobs created for more than 80% of the industries. This finding suggests that plants do not freeze employment adjustments given uncertainty shocks. Further, we relate the cumulative responses on variables reflecting industry-specific factor adjustment frictions, price rigidities, and financial frictions. We do not find evidence of factor adjustment frictions nor price rigidities as channels by which uncertainty affects job flows. On the contrary, financial frictions surges as an important mechanism.

Chapter 4. The last chapter of this thesis focuses on workers' heterogeneity. We explore the evolution of labor market income risk over the last three decades in the United States. We distinguish between risk resulting from idiosyncratic shocks to a worker's productivity, and the risk arising from jobs paying heterogeneous wages for the same worker. In order to identify these components empirically, we explicitly model workers' endogenous responses to these shocks.

Using panel data from the Survey of Income and Program Participation (SIPP) for males over the period 1983-2013, we find that differentiating between different types of risk and accounting for selection is important. While the variance of permanent risk has increased, on average, 40% across education groups, heterogeneity in job offers increased only for workers with at least some college education.

Finally, we quantify the role that changes in risk play in explaining rising wage inequality and their consequences for social welfare. We develop a structural partial equilibrium model where workers' productivity evolves stochastically, and face search frictions for finding jobs which pay heterogeneous wages for a given productivity level. The government and workers' precautionary savings provide partial insurance against income uncertainty. When simulating the increase in estimated risk, the model can account for almost all the rise in wage inequality during the last three decades. Yet, the overall welfare costs of rising wage uncertainty are small relative to the literature. Two main factors are important for this result. First, workers with higher educational degree compensate an increase of permanent risk with more dispersed job offers, which creates an option value to the worker. Second, the government plays a crucial role in insuring low educated workers. Welfare losses from changing wage risk would be about five times larger at these workers if government insurance would not be present.

2

Productivity Dispersions: Could it Simply be Technology Choice?

Joint with Christian Bayer and Matthias Meier

2.1 Introduction

The allocation of factors to their most productive use is often seen as one of the key determinants of economic prosperity (Foster et al., 2008). While first-best efficiency requires that factors produce the same marginal revenue across all production units, many studies show this condition to be violated in micro-data: factor productivities differ substantially within industries.[1]

We ask whether these micro-level differences can be understood as a result of frictions in technology choice; a setup, where firms may in principle choose from a broad set of technologies, but it is costly to search for them, to install them, and to acquire the know-how necessary to use them. This leads firms to operate one single technology which they adjust only occasionally. In between adjustments, production technology is Leontief. In particular, the capital-labor ratio, the capital intensity, remains fixed. As the economic environment changes and firms asynchronously adapt their technology in response, cross-sectional differences in factor productivities and capital intensity emerge.

[1] See Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Peters (2013), Asker et al. (2014), Gopinath et al. (2015), and Restuccia and Santaeulalia-Llopis (2015) to name a few.

This, however, is not the only empirical implication of frictional technology choice. Across all firms, differences in factor productivities and capital intensity should be predominantly long-lived. Moreover, there must be a trade-off involved. Firms with persistently high productivity in one factor should have a persistently low productivity in another factor. Further, as long as capital intensity is fixed, i.e. in the short run, labor and capital productivity can only move in the same direction. Finally, the extent of competition limits the scope of technologies used in the economy. The more competitive the environment, the larger is the pressure to abandon particularly cost-inefficient technologies.

To explore whether these implications are borne out empirically, we compute micro-level labor and capital productivity controlling for industry and time effects, and decompose them into their persistent and transitory components. To have a broad empirical base, we exploit micro data from Germany (firm-level), Chile, Colombia, and Indonesia (plant-level). Between 61% and 94% of the cross-sectional variance in labor and capital productivity is explained by their persistent components. The result is even stronger for capital intensity where the fraction explained by the persistent component is above 77% for all countries. Furthermore, the persistent components of labor and capital productivity are negatively correlated, while their transitory components are positively correlated. In addition, persistent differences in capital intensity are less dispersed in more competitive environments, i.e. where markups are persistently lower. Firms/plants in the most competitive quintile exhibit a 30-50% lower variance of capital intensity than those in the least competitive quintile. In summary, the data qualitatively supports the idea of a friction in technology choice driving productivity dispersions.

We use this framework to quantify the effects of a frictional technology choice in aggregate productivity. Despite the large cross-sectional productivity dispersion, our estimated efficiency losses from misallocation are on average 5%, which is small relative to the estimates from the literature. Important for this is our focus on productive efficiency, i.e. deviations from optimal capital intensity. In contrast, studies like Hsieh and Klenow (2009) have taken a broader focus including allocative efficiency, i.e. deviations from optimal scale. We disregard those deviations, showing up as dispersions in markups, for our efficiency calculations for two reasons. First, these dispersions might reflect efficient differentiation within industry. For example, they might stem from alternative strategies on product quality or range (e.g. Bar-Isaac et al., 2012), think of generics vs. patented pharmaceuticals. Second, there is already a broad set of theories predicting markup dispersions to which we have little to add. Think models with price setting frictions á la Calvo (1983), with building a customer base (Gourio and Rudanko, 2014), or with entry dynamics and innovation as in Peters (2013). All of these provide explanations of productivity dispersions through heterogeneous markups as endogenous objects. At the same time, our data suggests that markup dispersions themselves explain only a minority of all productivity dispersion.

Our results are linked to the traditional putty-clay assumption (Johansen, 1959), which has been advocated to address a broad array of other empirical phenomena (Gilchrist and Williams, 2000, 2005; Gourio, 2011). Particularly closely related is Kaboski's (2005) model of putty-clay technology choice under factor price uncertainty. An important insight from this paper that carries over to our setup is that firms underreact to current prices in setting their technology, such that the regression techniques usually used to identify the long-run elasticity of substitution (see e.g. Raval (2014) or Oberfield and Raval (2014) for recent contributions or Chirinko (2008) for an overview) are subject to a downwards bias. In fact, we provide evidence that this downwards bias is likely substantial. This high elasticity not only has important implications for income-shares (see e.g. Solow, 1956; Piketty, 2011; Piketty, 2014; Karabarbounis and Neiman, 2013) but is also key to compute the efficiency losses from a friction in technology choice.

The remainder of this paper is organized as follows: Section 2.2 describes our technology choice model in a simplified two-period setup. This allows us to derive the main qualitative insights that we have sketched in this Introduction and guides our empirical analysis in Section 2.3. Section 2.4 presents potential gains from eliminating this friction, and Section 2.5 concludes. An Appendix follows.

2.2 Technology Choice Model

To guide our empirical analysis we consider a two-period technology choice model. We assume a mass of firms of measure one. Each firm, i, is endowed with one plant that has an exogenously given capital intensity $k_i = \frac{K_i}{N_i}$, where K_i is the physical amount of capital and N_i is labor. Furthermore, wages, W, and user costs of capital, R, are exogenously given, but stochastic.

2.2.1 Output choice

Each firm has a constant returns to scale production technology and faces monopolistic competition for its product, where the elasticity, ξ_i, of demand for the product, y_i, of firm i is firm-specific and constant, such that prices are given by

$$p_i = \frac{1}{1-\xi_i} z_i^{\xi_i} y_i^{-\xi_i},$$

where z_i is the stochastic market size for firm i's product. Unit costs of production depend on the plant's capital intensity and factor prices, $c_i = c(k_i, W, R)$. The firm maximizes profits, and we assume that the firm needs to decide about output before knowing actual factor prices and demand. The optimal policy will choose output in order to stabilize the expected markup at its optimal level. The expected gross markup is constant, $\frac{1}{1-\xi_i} > 1$. Denoting the expectations operator as $\mathbb{E}$, it is straightforward to show that the profit maximizing output, y_i^* and expected profits under the optimal policy, π^*, are given by

$$y_i^* = \left[\frac{\mathbb{E}z_i^{\xi_i}}{\mathbb{E}c(k_i, R, W)}\right]^{1/\xi_i}; \qquad \pi_i^* = \frac{\xi_i}{1-\xi_i} y_i^* \mathbb{E}c(k_i, R, W). \tag{2.1}$$

2.2.2 Revenue productivities

This implies that firms facing higher demand elasticities, ξ_i, have on average larger markups and larger revenue factor productivities. Deviations from expected costs, $\mathbb{E}c_i / c_i$, and deviations from expected demand, $z_i^{\xi_i} / \mathbb{E}z_i^{\xi_i}$, lead to additional fluctuations in realized markups, given by:

$$\frac{p_i y_i^*}{WN_i + Rk_i N_i} = \frac{1}{1-\xi_i} \frac{z_i^{\xi_i}}{\mathbb{E}z_i^{\xi_i}} \frac{\mathbb{E}c_i}{c_i}. \tag{2.2}$$

Similarly, splitting up this term in two components, these fluctuations move the capital and labor expenses per value added:

$$\frac{p_i y_i^*}{WN_i} = \frac{1}{1-\xi_i}\frac{z_i^{\xi_i}}{\mathbb{E}z_i^{\xi_i}}\frac{\mathbb{E}(W+Rk_i)}{W} \tag{2.3}$$

$$\frac{p_i y_i^*}{Rk_iN_i} = \frac{1}{1-\xi_i}\frac{z_i^{\xi_i}}{\mathbb{E}z_i^{\xi_i}}\frac{\mathbb{E}(W+Rk_i)}{Rk_i} \tag{2.4}$$

On the one hand, (2.3) and (2.4) show that firms with higher (target) markups, $\frac{1}{1-\xi_i}$ exhibit both higher labor and capital productivities. Similarly, positive and unforeseen demand shocks, $z_i^{\xi_i}/\mathbb{E}z_i^{\xi_i}$, increase both factor productivities. Importantly, in a more general multi-period setup, these deviations from expectations could only be transitory. On the other hand, firms with higher capital intensity have a lower capital and higher labor revenue-productivity, even when these capital intensity differences are expected.

To summarize, productivities differ across firms either because of differences in size relative to demand (the first two terms) or due to differences in capital intensity and factor prices (the last term) in (2.3) and (2.4).[2]

2.2.3 Choice of technology

We assume that in the period preceding production, the firm can opt to replace its existing plant, setting up a new one with different capital intensity k. In doing so, the firm compares expected profits with and without technology adjustment to decide the period preceding production whether to produce with its initially given capital intensity or to invest in changing the technology. We assume adjustment is costly as it disrupts production. This disruption summarizes all costs of searching for a technology, installing it and learning to operate it. Upon adjustment the firm forgoes a fraction ϕ_i of next period's profits, where ϕ_i stochastic and drawn from a distribution Φ. The firm draws ϕ_i before it decides about adjustment and hence adjusts capital intensity to $\hat{k}$, the capital intensity that minimizes expected unit costs, whenever

[2] As evident from equation 2.2, in this environment, adding an additional shock to unit costs (a TFP shock) has the same implications as a demand shock.

$(1-\phi_i)E\pi(\hat{k}) > E\pi(k_i)$. This simplifies to

$$(1-\phi_i) > \left(\frac{\mathbb{E}c(k_i,R,W)}{\mathbb{E}c(\hat{k},R,W)}\right)^{\frac{\xi_i-1}{\xi_i}}, \tag{2.5}$$

using the expressions in (2.1) for expected profits.

Since $\frac{\mathbb{E}c(k_i,R,W)}{\mathbb{E}c(\hat{k},R,W)} \geq 1$, firms with higher elasticity of demand, ξ_i, are less likely to adjust for a given ex ante capital intensity k_i. The reason is that firms with high market power can offload their higher unit costs to consumers and hence have less incentive to invest in efficient capital intensities. This is reminiscent of Leibenstein's (1966) X-inefficiency of monopolies or Bester and Petrakis's (1993) results for oligopolies.[3]

As a result, ex-post capital-intensity will be less dispersed within the group of firms with low markups than among high-markup firms if the ex-ante distribution of capital intensities is centered around the cost minimizing level $\hat{k}$.

2.2.4 Unit costs

To specify more concretely the relation between capital intensity and unit costs, we assume that the long-run technology is given by a constant elasticity of substitution (CES) production function with substitution elasticity σ, such that the output of a plant with capital intensity k_i is given by

$$y_i = \left[\alpha k_i^{\frac{\sigma-1}{\sigma}} + (1-\alpha)A^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} N_i, \tag{2.6}$$

where A captures (Harrod neutral) labor-augmenting technological change, and α is the distribution parameter.

This implies that *realized* unit costs, $c_i = \frac{Rk_iN_i+WN_i}{y_i}$ are minimal at capital intensity k^*, given by

$$k^* = \left[\frac{\alpha}{1-\alpha}\frac{W}{R}\right]^{\sigma} A^{1-\sigma}. \tag{2.7}$$

[3] There is, however, one interesting side result of our setup. One can easily show that under the specific assumption of an isoelastic demand curve and monopolistic competition, producer profits and consumer rents are equal and therefore, total social surplus of adjustment as well as the social costs of adjustment need to be scaled by factor two such that the individual optimal adjustment choice is socially optimal.

Now, to obtain an expression that allows us to relate the cross-sectional average unit costs to the first two moments of the capital intensity distribution, we use a log second-order approximation around that minimum:

$$\mathbb{E}^x\left[\log\frac{c(k_i,R,W)}{c(k^*,R,W)}\right] \approx \frac{1}{2\sigma}s^*(1-s^*)\left\{\left[\mathbb{E}^x\left(\log\frac{k_i}{k^*}\right)\right]^2 + \mathbb{V}^x(\log k_i)\right\}, \qquad (2.8)$$

where s^* is the capital expenditure share in the cost-minimizing optimum[4]

$$s^* = Rk^*/(W + Rk^*),$$

and $\mathbb{E}^x$ denotes the cross-sectional average and $\mathbb{V}^x$ the cross-sectional variance. In words, the efficiency loss is composed of the average relative difference of capital intensity from its optimum, $\mathbb{E}^x\log(k_i/k^*)$, and the cross-sectional dispersion of capital intensity across plants, $\mathbb{V}^x(\log k_i)$. Importantly, the higher the elasticity of substitution between labor and capital, σ, the lower the efficiency loss from not re-setting capital intensities to their optimum.

2.3 Empirics

2.3.1 Data description

We document factor productivity and capital intensity dispersion in firm-level data from Germany, and plant-level data from Chile, Colombia and Indonesia. For Germany, we use the balance sheet data base of the Bundesbank, USTAN, which is a private sector, annual firm-level data available for 26 years (1973-1998).[5] For Chile, Colombia and Indonesia, we have plant level data from the ENIA survey for 1995-2007, the EAM census for 1977-1991 and the IBS dataset for 1988-2010, respectively. These datasets are focused on the manufacturing sector, with the exception of Germany, which provides information for the entire private non-financial business sector.[6]

[4] See Appendix 2.A.2 for details.
[5] See Bachmann and Bayer (2014) for a detailed description.
[6] In particular, private non-financial business sector includes Agriculture, Energy and Mining, Manufacturing, Construction, and Trade.

When preparing the data for our analysis, we make sure to treat them in the most comparable way. From each survey, we use a firm's/plant's four-digit industry code, wage bill, value-added and book or current value of capital stock. In order to obtain economically consistent capital series for each firm/plant, we re-calculate capital stocks using the perpetual inventory method when the data set does not include estimates of the capital stock at current values. When recalculating the capital stock, we exploit information of capital disaggregated into structures and equipment, which allows us to control for heterogeneity in capital composition across plants.

Our capital productivity measure requires information on the real interest rate and economic depreciation. For the latter, we do not rely on the depreciation reported by plants, that is potentially biased for tax purposes, but instead use economic depreciation rates obtained from National Statistics or external studies if the former is not available and take the different capital good mixes across firms/plants into account. Since it is hard to identify the right measure for a real rate for the developing economies, we instead fix the real rate to 5% for all economies. This implies user costs of capital $R_{it} = 5\% + \delta_{it}$.[7] In generating cross-sectional statistics, time variations in user costs are controlled for by taking out four-digit industry-year fixed effects. The data treatment and sample selection is described in detail in Appendix 2.A.1.2.

2.3.2 Productivities and their transitory and persistent component

We compute average factor productivities for capital and labor per firm and year using the reported value added per firm/plant at current prices, $p_{it}y_{it}$, labor expenses, W_tN_{it} as reported in the profit and loss statements, and imputed capital expenses, $R_{it}K_{it}$. Taking logs, we define revenue productivities of labor and capital

$$\alpha_{it}^N \; := \; \log(p_{it}y_{it}) - \log(W_tN_{it}); \qquad \alpha_{it}^K \; := \; \log(p_{it}y_{it}) - \log(R_{it}K_{it}). \tag{2.9}$$

[7] The economic depreciation rate of equipment and structures for Germany is obtained from *Volkswirtschaftliche Gesamtrechnung* (VGR) while for Chile we obtain time series from Henriquez (2008). Finally, as for Colombia and Indonesia, we consider the average depreciation in Chile for the available period given the absence of national data sources. The depreciation rate values are 15.1% (equipment) and 3.3% (structures) in Germany, while they are on average 10.5% (equipment) and 4.4% (structures) for the rest of the countries.

Using expenditures and value added implicitly controls for quality differences in both inputs and outputs (c.f. Hsieh and Klenow, 2009). In addition, we construct markups as value added relative to total expenditures on labor and capital

$$mc_{it} \;:=\; \log(p_{it}y_{it}) - \log(R_{it}K_{it} + W_t N_{it}). \tag{2.10}$$

Finally, we calculate the price weighted capital intensity,

$$\kappa_{it} \;:=\; \log(R_{it}K_{it}) - \log(W_t N_{it}). \tag{2.11}$$

For any of these variables, say x_{it}, we calculate 5-year moving averages, denoted $\bar{x}_{it} := \frac{1}{5}\sum_{s=-2}^{2} x_{it+s}$, to identify the persistent component and deviations thereof, $\hat{x}_{it} := x_{it} - \bar{x}_{it}$, to identify the transitory component.

We then take out four-digit industry-year fixed effects and calculate dispersions and correlations between the factor productivities for each component.

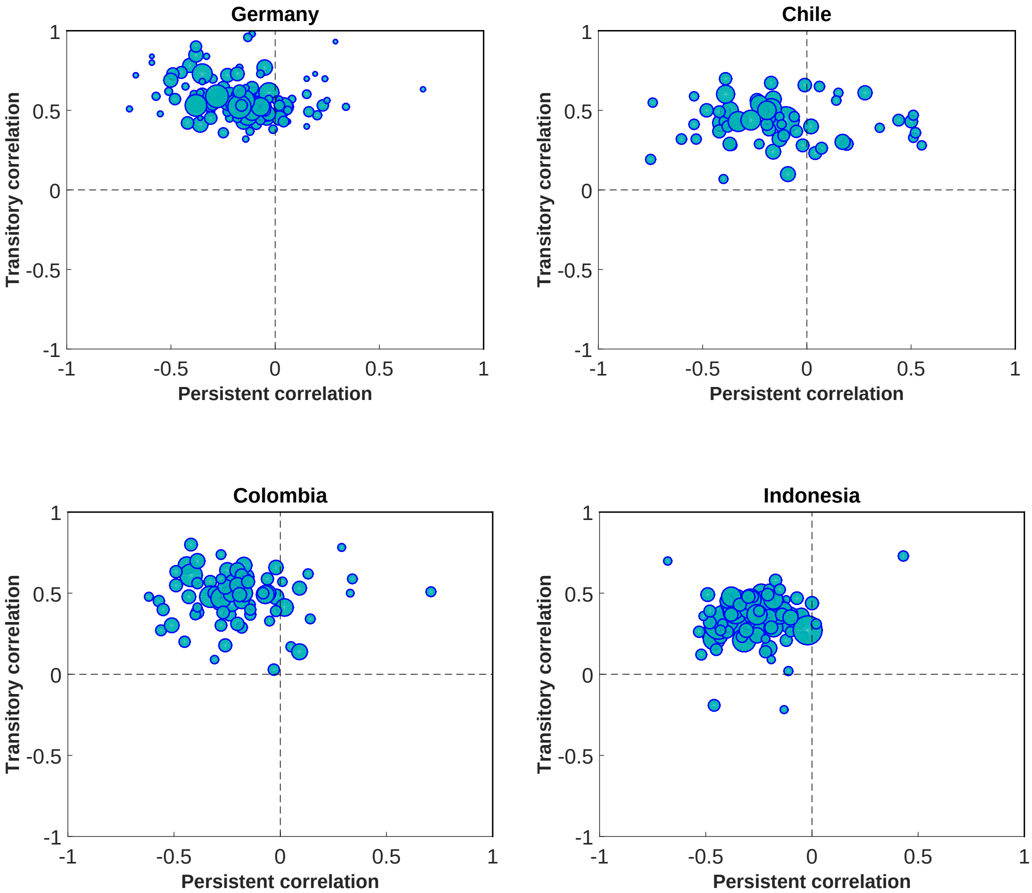
2.3.3 Empirical findings

Table 2.1 reports standard deviations and correlation for labor and capital productivity and for all four countries. Three observations stand out: First, capital and labor productivity are positively correlated in the transitory component ($\rho \approx 40\%$) while they are negatively correlated in the persistent component ($\rho \approx -20\%$). Using the expressions for factor productivities in Section 2.2, see (2.3) and (2.4), deviations from optimal size are more important in the short run, while deviations from optimal capital intensity are more important in explaining long-run productivity differences. Second, the persistent components in productivity explain the vast majority of cross-sectional productivity differences (between 60% and 92% for labor and between 79% and 94% for capital). Third, the developing economies show larger productivity dispersions.

As the positive/negative correlation pattern between labor and capital productivity is a particularly important prediction of technology choice, we check whether this pattern holds within the four-digit industries. Figure 2.1 shows that this is the case for the vast majority of industries.

In light of our results in Section 2.2, it is useful to look at markup and capital intensity differences, see Table 2.2. In particular, (2.8) allows us to relate the latter

Figure 2.1. Correlations of factor productivities by four-digit industry



Notes: *Transitory (Persistent) Correlation*: Correlation between the transitory (persistent) component of labor and capital productivity at the firm/plant level, controlling for time-fixed effects. Each circle represents a four digit industry, where the size of a circle reflects aggregate employment in that industry. For this figure, we restrict industries to include at least 20 firms/plants. The number of industries inside the upper-left quadrant is 99 (out of 125) in Germany, 45 (out of 61) in Chile, 62 (out of 73) in Colombia, and 85 (out of 90) in Indonesia.

Table 2.1. Transitory and persistent components of factor productivities

	$\text{std}(\hat{\alpha}^L_{it})$	$\text{std}(\hat{\alpha}^K_{it})$	$\rho(\hat{\alpha}^L_{it}, \hat{\alpha}^K_{it})$	$\text{std}(\bar{\alpha}^L_{it})$	$\text{std}(\bar{\alpha}^K_{it})$	$\rho(\bar{\alpha}^L_{it}, \bar{\alpha}^K_{it})$
	Transitory Component			Persistent Component		
DE	0.066	0.119	0.352	0.229	0.456	-0.207
	(0.000)	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)
CL	0.184	0.281	0.449	0.232	0.577	-0.190
	(0.006)	(0.008)	(0.017)	(0.009)	(0.028)	(0.021)
CO	0.144	0.172	0.517	0.257	0.568	-0.234
	(0.003)	(0.004)	(0.012)	(0.008)	(0.023)	(0.018)
ID	0.211	0.369	0.343	0.255	0.669	-0.269
	(0.003)	(0.005)	(0.007)	(0.004)	(0.013)	(0.009)

Notes: Cross-sectional standard-deviations (std) and correlation (ρ) of transitory and persistent components of labor- and capital productivity, α^L_{it} and α^K_{it} as in (2.9). DE: Germany, CL: Chile, CO: Colombia, ID: Indonesia. Transitory and persistent components are obtained by applying a five year moving average filter. Factor productivities are demeaned by 4-digit industry and year, and expressed in logs. In parentheses: Clustered standard errors at the firm/plant level.

directly to increases in unit costs. For all countries, differences in capital intensity are very persistent. The transitory component makes up only between 4% (Germany) and 17% (Indonesia) of the total variance. At the same time, persistent differences in capital intensity are substantially more dispersed in Chile, Colombia, and Indonesia than they are in Germany with variances being twice as high in Indonesia than in Germany.

On the contrary, the dispersion of persistent cross-sectional markup differences is strikingly similar across countries, and transitory differences in markups are an important component of the total cross-sectional variance of markups – at least in the developing economies (30% in Colombia, 50% in Chile and Indonesia) but less so in Germany (12%).[8]

[8] This might relate to the fact that demand is less stable in the developing economies. In fact, the cross-sectional standard deviation of value-added growth is two to four times larger in these economies than in Germany.

Table 2.2. Transitory and persistent components of markup and capital intensity

	std($\hat{mc}_{it}$)	std($\hat{\kappa}_{it}$)	$\rho(\hat{mc}_{it}, \hat{\kappa}_{it})$	std($\bar{mc}_{it}$)	std($\bar{\kappa}_{it}$)	$\rho(\bar{mc}^{L}_{it}, \bar{\kappa}_{it})$
	Transitory Component			Persistent Component		
DE	0.064	0.114	-0.155	0.172	0.551	0.062
	(0.000)	(0.001)	(0.002)	(0.001)	(0.004)	(0.004)
CL	0.177	0.258	-0.090	0.184	0.661	-0.085
	(0.005)	(0.009)	(0.017)	(0.005)	(0.029)	(0.022)
CO	0.134	0.157	-0.016	0.206	0.676	-0.232
	(0.003)	(0.004)	(0.012)	(0.005)	(0.025)	(0.018)
ID	0.203	0.357	-0.120	0.195	0.778	-0.021
	(0.002)	(0.005)	(0.007)	(0.003)	(0.014)	(0.010)

Notes: Capital intensities, κ_{it}, and markups, mc_{it}, as defined in (2.10) and (2.11). See notes of Table 2.1 for further explanation.

These results along with (2.3) and (2.4) suggest that an important component in the persistent differences in productivity is the choice of capital intensities; deviations in optimal scale being important but minor.

To understand to what extent firms actively take these unit cost increases into account, we split the sample according to firm/plant characteristics – age, size, and importantly a firm's average markup – and compute again the dispersions of the persistent component of capital intensity, see Table 2.3. While there are some differences in these dispersions according to age and size, these are neither large nor systematic. What stands out is splitting the sample according to the average markup. The highest markup quintile exhibits between 30% and 60% higher capital intensity dispersions (in terms of variances) than the lowest markup quintile. This is in line with the qualitative predictions of our model.

We framed our empirical analysis based on a frictional technology adjustment economy. Yet, could the observed dynamics be rationalized by factor adjustment frictions? In Appendix 2.A.3 we show that a dynamic model of capital adjustment costs calibrated to the German economy is unable to explain our empirical results. While this model can explain the overall dispersion in factor productivities, the model gen-

Table 2.3. Persistent component of capital intensity by firm/plant characteristics

	std($\bar{\kappa_{it}}$)					
	Markups		Size		Age	
	Bottom Quintile	Top Quintile	Bottom Quintile	Top Quintile	Young	Old
DE	0.545 (0.010)	0.622 (0.010)	0.610 (0.009)	0.509 (0.011)	n.a.	n.a.
CL	0.568 (0.042)	0.713 (0.075)	0.749 (0.068)	0.622 (0.058)	n.a.	n.a.
CO	0.547 (0.035)	0.694 (0.061)	0.763 (0.051)	0.669 (0.061)	0.697 (0.100)	0.699 (0.048)
ID	0.716 (0.028)	0.834 (0.035)	0.830 (0.034)	0.816 (0.035)	0.770 (0.058)	0.801 (0.038)

Notes: Bottom (top) markup quintile: firm/plant average markup below the 20th percentile (above the 80th percentile). Old (young): Plant age below 4 years (above 15 years). Bottom (top) size quintile: firm/plant average employment below the 20th percentile (above 80th percentile). The micro data from Germany and Chile does not include age. See notes of Table 2.1 and 2.2 for further explanation.

erates long-lived differences in capital productivity that are too small compared to our empirical results and short-lived differences that are too large. In addition, the correlations between labor and capital productivity show the wrong signs when we split it into transitory and persistent components. This result is common to any model with different degrees of flexibility in labor and capital. When one factor is more flexible than the other, a firm will use the more flexible factor strongly to accommodate shocks to its optimal scale.

2.3.4 Robustness

We conduct some robustness checks based on our baseline results from section 2.3.3. First, we show that our empirical findings are robust to alternative way of decomposing into transitory and persistent components (Table 2.4), and to weighting of the moments (Table 2.5). We also show that persistent capital intensity differences are more dispersed for high-markup firms/plants even controlling for size and age (Table 2.6). To compute the latter, we first remove cross sectional differences in log capital intensity that can be explained by markups, size and age in logs. Finally, the variance of the unexplained component from first stage is regressed as a function of the standarized markups, size and age in logs. For all countries, except Colombia, markups are as important as size for explaining persistent differences in capital-intensity.

Table 2.4. Robustness: Transitory and persistent components (HP-filtered) of factor productivities, markups, and capital intensity

	std($\hat{\alpha}^L_{it}$)	std($\hat{\alpha}^K_{it}$)	$\rho(\hat{\alpha}^L_{it}, \hat{\alpha}^K_{it})$	std($\bar{\alpha}^L_{it}$)	std($\bar{\alpha}^K_{it}$)	$\rho(\bar{\alpha}^L_{it}, \bar{\alpha}^K_{it})$
	Transitory Component (HP)			Persistent Component (HP)		
DE	0.062	0.113	0.352	0.236	0.471	-0.223
CL	0.169	0.260	0.447	0.231	0.578	-0.191
CO	0.134	0.159	0.516	0.257	0.569	-0.234
ID	0.196	0.343	0.344	0.256	0.670	-0.270

	std($\hat{mc}_{it}$)	std($\hat{\kappa}_{it}$)	$\rho(\hat{mc}_{it}, \hat{\kappa}_{it})$	std($\bar{mc}_{it}$)	std($\bar{\kappa}_{it}$)	$\rho(\bar{mc}_{it}, \bar{\kappa}_{it})$
	Transitory Component (HP)			Persistent Component (HP)		
DE	0.073	0.134	-0.184	0.157	0.490	0.089
CL	0.183	0.295	-0.123	0.152	0.552	-0.097
CO	0.145	0.186	-0.066	0.178	0.594	-0.230
ID	0.207	0.412	-0.130	0.160	0.672	-0.027

Notes: Labor productivity, a^L_{it}, and capital productivity, a^K_{it}, as defined in (2.9). Markups, mc_{it}, and capital intensity, κ_{it}, as defined in (2.10) and (2.11). HP: results based on the decomposing between transitory and persistent using a HP-filter ($\lambda = 6.25$). Factor productivities are demeaned by 4-digit industry and year and expressed in logs. Standard errors are clustered standard errors at the firm/plant level. ρ denotes correlation. DE: Germany, CL: Chile, CO: Colombia, ID: Indonesia.

Table 2.5. Robustness: Weighted second moments of factor productivities, markups, and capital intensity at different frequencies

	std($\hat{\alpha}^L_{it}$)	std($\hat{\alpha}^K_{it}$)	$\rho(\hat{\alpha}^L_{it}, \hat{\alpha}^K_{it})$	std($\bar{\alpha}^L_{it}$)	std($\bar{\alpha}^K_{it}$)	$\rho(\bar{\alpha}^L_{it}, \bar{\alpha}^K_{it})$
	Transitory Component (5Y MA)			Persistent Component (5Y MA)		
DE	0.050	0.101	0.316	0.196	0.457	-0.176
CL	0.187	0.281	0.457	0.239	0.551	-0.205
CO	0.143	0.170	0.520	0.260	0.562	-0.239
ID	0.216	0.370	0.349	0.263	0.672	-0.275
	std($\hat{mc}_{it}$)	std($\hat{\kappa}_{it}$)	$\rho(\hat{mc}_{it}, \hat{\kappa}_{it})$	std($\bar{mc}_{it}$)	std($\bar{\kappa}_{it}$)	$\rho(\bar{mc}_{it}, \bar{\kappa}_{it})$
	Transitory Component (5Y MA)			Persistent Component (5Y MA)		
DE	0.052	0.090	-0.161	0.172	0.503	0.067
CL	0.179	0.259	-0.090	0.183	0.645	-0.087
CO	0.133	0.155	-0.016	0.209	0.670	-0.237
ID	0.207	0.356	-0.123	0.198	0.787	-0.021

Notes: abor productivity, a^L_{it}, and capital productivity, a^K_{it}, as defined in (2.9). Markups, mc_{it}, and capital intensity, κ_{it}, as defined in (2.10) and (2.11). Cross-sectional standard-deviations (std) and correlation (ρ) of transitory and persistent components. Transitory and persistent components are obtained by applying a five year moving average filter (5Y MA). Moments are weighted based on the value-added of the plant/firm. Variables under interest are demeaned by 4-digit industry and year and expressed in logs. Standard errors in parentheses are clustered standard errors at the firm/plant level. DE: Germany, CL: Chile, CO: Colombia, ID: Indonesia.

2.4 Efficiency losses from a friction in technology choice

We consider the framework from Section 2.2 and the empirical results from Section 2.3 to quantify the efficiency losses from frictional technology choice. To do so, we require an estimate of the capital share in each economy and the elasticity of substitution between labor and capital.

Table 2.6. Robustness: Regression on the variance in the unexplained persistent component of capital intensity

	DE	CL	CO	ID
	$var(\epsilon_{\tilde{\kappa}_{it}})$			
Log-Markup	0.024	0.069	0.036	0.057
	(0.003)	(0.017)	(0.019)	(0.011)
Log-Size	-0.026	-0.068	-0.057	0.017
	(0.003)	(0.017)	(0.024)	(0.015)
Log-Age		-	0.044	0.009
		-	(0.018)	(0.011)

Notes: The results are obtained based on a two step procedure. First, we remove cross sectional differences in log capital intensity (κ) that can be explained by the demeaned log of markups, size and age. Second, the variance of the estimated residual based on the first stage ($\epsilon_{\tilde{\kappa}_{it}}$), is regressed as a function of the standarized log of markups, size and age. Standard errors in parentheses are clustered standard errors at the firm/plant level. DE: Germany, CL: Chile, CO: Colombia, ID: Indonesia.

We compute the capital share based on the ratio of capital expenditures to total expenditures from our micro-data, while we estimate the elasticity of substitution based on country-panel data from Feenstra et al. (2015).[9]

The elasticity of substitution between labor and capital can be recovered from time-series information of the aggregate capital intensity and the relative factor price. In a frictionless economic environment, the parameter is determined by the contemporaneous regression between these variables. However, the identification is problematic under the presence of frictions which prevents immediate adjustment of production factors. Consequently, the contemporaneous reaction from exogenous price movements (short-run elasticity) differs from the final target (long-run elasticity).

In order to uncover the long-run elasticity of substitution, we instrument observed relative factor prices with the top marginal income tax rate on domestic corporations

[9] We obtain a capital share of 21% (Germany), 40% (Colombia), 32% (Chile), and 23% (Indonesia).

Table 2.7. Estimation of long-run elasticity of substitution

	Dependent variable: $\log\left(\frac{K}{N}\right)$		
$\log\left(\frac{W}{R}\right)$	0.68 (0.01)	0.43 (0.01)	1.28 (0.35)
Constant	39.41 (1.82)	19.40 (1.40)	135.97 (48.24)
Trend	Yes	Yes	Yes
Country fixed effects	No	Yes	Yes
Instrument	No	No	Yes
R^2	0.76	0.75	0.71
Countries	99	99	99
Obs	2609	2609	2609

Notes: Regressions based on country panel data for the period 1956-2002. Period length differs by country due to data availability. We instrument relative factor price using the top marginal income tax rate on domestic corporations at the country level. Standard errors in parenthesis.

at the country level.[10] As our instrumental variable is highly persistent, we capture movements in factor prices that are long-lived, and thus, we obtain a closer approximation to the long-run elasticity of substitution.[11]

Table 2.7 provides the results from this exercise. Once we instrument the relative factor price with corporate taxes, we obtain an estimated elasticity of 1.28. As argued before, the simple contemporaneous regression would imply a 50% lower estimated elasticity.

Based on these estimates, we compute the efficiency losses from a friction in technology choice. On average, unit costs increase, on average, by 5% compared to

[10] Given that we do not have information on real interest rate from all countries in the World, we approximate the risk-free interest rate using the Federal Funds rate (yearly average). We consider country panel data on labor, capital, and hourly wage from Feenstra et al. (2015). We impute hours worked at those countries with missing information by the average hours worked at each year based on those countries with available data. Finally, we construct tax series using the World tax Database available at http://www.bus.umich.edu/otpr/otpr/default.asp.

[11] Alternatively, the literature aims to estimate the long-run elasticity of substitution using cointegration properties, cross country variation in the trends of factor prices, or low-pass filter. See Chirinko (2008) for more details.

their minimum obtained by always setting capital intensity to the optimal level, the values range goes from 2.5% in Germany to 6.3% in Indonesia.

Notice that our estimates of efficiency losses do not consider in the calculation the time-series component $\left(E_t^x \log k_{it} - \log k^*\right)^2$. To do so, we require a dynamic version of the model described in Section 2.2. Therefore, our estimates constitute a lower bound of the potential efficiency losses from a friction in technology choice.

2.5 Conclusion

This paper asks whether productivity dispersions should be understood as a result of frictions in technology choice. We have derived qualitative implications of such friction and show that these are borne out empirically.

In line with the existing literature, we find large productivity differences across firms/plants even within narrowly defined industries. We show that most of the differences are long lived and related to highly persistent differences in capital intensity. Despite the strong relative differences across countries our estimated efficiency losses from a friction in technology choice are, on average, 5%.

For future work it would be important to explore whether a dynamic model of technology choice is able to explain our empirical results not only qualitatively, but also quantitatively. This model would allows us to account for all components driving the efficiency losses from a friction in technology choice.

Appendix 2.A Appendix

2.A.1 Empirics

2.A.1.1 Description of the data

German Firm Data: USTAN (Unternehmensbilanzstatistiken)

USTAN is itself a byproduct of the Bundesbank's rediscounting and lending activity. The Bundesbank had to assess the creditworthiness of all parties backing promissory notes or bills of exchange put up for rediscounting (i.e. as collateral for overnight lending). It implemented this regulation by requiring balance sheet data of all parties involved, which were then archived and collected, see Bachmann and Bayer (2013) for details. Our initial sample consists of 1,846,473 firm-year observations. We remove observations from East German firms to avoid a break of the series in 1990. Finally, we drop the following sectors: hospitality (hotels and restaurants), financial and insurance institutions, public health and education sectors. The resulting sample covers roughly 70% of the West-German real gross value added in the private non-financial business sector. In particular, it includes Agriculture, Energy and Mining, Manufacturing, Construction, and Trade.

Chilean Plant Data: ENIA (Encuesta Nacional Industrial Anual)

ENIA is collected by the National Institute of Statistics (*Instituto Nacional de EstadÃŋsticas*, INE) and provides plant-level data from 1995 to 2007. ENIA contains information for all manufacturing plants with total employment of at least ten. For the period under analysis, we have a sample of 70,217 plant-year observations. According to INE, this sample covers about 50% of total manufacturing employment.

Colombian Plant Data: EAM (Encuesta Anual Manufacturera)

EAM is a plant-level survey collected by National Institute of Statistics (*Departamento Administrativo Nacional de Estaditicas*, DANE) for the period 1977 to 1991. The survey covers information for all manufacturing plants during 1977-1982, while it only contains data on plants above 10 employees for 1983-1984, and from 1985, small plants are included in small proportion. This results in 103,011 plant-year observations.

Indonesian Plant Data: IBS (Survei Tahunan Perusahaan Industri Pengolahan)

IBS is the Indonesian Manufacturing Survey of Large and Medium Establishments, provided by the National Institute of Statistics (*Badan Pusat Statistik*, BPS). The survey covers all plants with 20 or more employees in the manufacturing sector. Given that the capital stock is reported since 1988 onwards, we exclude earlier years and focus on the period 1988-2010, with 485,052 plant-year observations.

2.A.1.2 Sample selection

Starting from the raw data set, we concentrate on describing the general cleaning steps common to all countries, and we provide more information about country-specific cleaning steps at Table 2.8.

To begin with, we remove observations where firms or plants report extraordinarily large depreciation rates (e.g. due to fire or accident). The reason is that our dynamic model does not capture such cases, and the perpetual inventory method (PIM) will inaccurately measure the actual capital stock after such incidents occur.[12] Next, for those countries where current values of capital stock is not provided (Germany and Colombia), we recompute capital stocks using the PIM. In conducting the PIM, we drop a small amount of outliers, as explained in Section 2.A.1.4. Further, we do not consider observations where value-added, capital stock, or employment is non-positive or missing.

Moreover, we do not consider observations where firms/plants have missing values in the changes of employment (N), real capital (K) and real value-added (VA).[13] To construct capital productivity, we use the lagged value of capital stock, so we effectively discard the first year of each micro unit. We remove outliers in the levels and in the relative changes of employment, capital, value-added, and factor shares based on 3 standard deviations from the industry-year mean. In addition, we drop firm/plant-year observations whenever the total factor expenditures share is either below 1/3 or above 3/2, and whenever the firm/plant average total factor expenditure share is above 1. These two cleaning steps should exclude units from our analysis which report continuously unreasonably large markups or losses.

Finally, as our empirical results rely on a 5-year moving average filter, we do not consider firm/plant-year observations that have less than 5 consecutive years.

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[12] At some cases in the ENIA, EAM, and IBS surveys, plants do not report depreciation conditional on positive capital stock. In order to not loose this observations, we impute the depreciation by capital type and two-digit industry, estimating a random effect model, using as explanatory variable the log-capital stock. To discard rare depreciation events, we drop observations whenever the reported depreciation rate in structures (equipment) is above 40% (60%) yearly. Additionally, we do not consider those cases where the reported depreciation is below 0.1% (1%) in structures (equipment), yearly.

[13] To construct measures of real capital stock we consider an index price by each capital type (when available) using the information of gross fixed capital formation at current and constant prices from National Accounts, while for for value added we use the GDP price deflator.

Table 2.8. Sample selection

Criterion/Country	Germany	Chile	Colombia	Indonesia
Initial sample	1,846,473	70,217	103,006	485,052
East Germany	-115,201	–	–	–
Additional cleaning steps	–	–	–	-32,618
Imputation capital stock	–	–	–	+37,341
Rare depreciation events	-54,280	-8,197	-6,176	-8,775
Outliers in PIM	-73,784	–	-4,280	–
Missing values	-422,739	-19,589	-29,804	-235,280
Outliers in factor variables	-176,232	-12,375	-24,651	-86,070
Less than 5 consecutive years	-312,452	-15,479	-14,264	-84,885
Final sample	689,665	14,307	23,831	74,765

Notes: Missing values denote the sum of missing values at log value added, log capital, factor shares and log changes in employment, capital and value added. Outliers in factor variables is the sum of all identified outliers at log changes in employment, real capital and real value added, and factor shares. For more information with respect to *Additional cleaning steps* and *Imputation of capital stock* in Indonesia, see Section 2.A.1.3.

2.A.1.3 Specific cleaning and imputation steps for IBS

Before proceeding with the general cleaning steps applied to all datasets, we need to implement some specific corrections at the Indonesian micro-data. In doing so, we closely follow Blalock and Gertler (2009). First, we correct for mistakes due to data keypunching. If the sum of the capital categories is a multiple of 10^n (with n being an integer) of the total reported capital, we replace the latter with the sum of the categories. Second, we drop duplicate observations within the year (i.e. observations which have the same values for all variables in the survey but differ in their plant identification number). Third, we re-compute value added whenever their values are not consistent with the formula provided by BPS. Finally, the survey changed their industry classification from ISIC Rev. 2 in 1998 to ISIC Rev. 3 in 1999 and to ISIC Rev. 4 in 2010. We use United Nations concordance tables to construct a consistent time series of four digit industry classification.

Further, the surveys from 1996 and 2006 provides only information on the aggregate capital stock, yet, not disaggregated by capital type (structure and equipment). To construct an economically reasonable estimate of these variables for these years, we use the average reported investment share and capital share of capital type in the preceding and subsequent year, and impute it, multiplying the aggregate capital stock and investment with the respective share.

Finally, we impute capital stock for plants, whenever the survey presents missing values for this variable in plants which reported information in previous and/or subsequent years. Following Vial (2006), we impute capital by type (machinery, vehicles, land and buildings), using the following regression by two-digit sectoral level:

$$\log K_{it} \;=\; \beta_0 + \beta_1 \log K_{it-1} + \theta \ln X_{it-1} + \mu_i + \epsilon_{it}$$

where K_{it} is the capital stock of type i, μ_i plant fixed effects and X_{it-1} a set of explanatory variables (total output, input, employees, wages, fuel costs and expenditures on materials, leasing, industrial services and taxes).[14]

2.A.1.4 Perpetual inventory method

Whenever the dataset does not directly provide information on a firm's/plant's capital stock at current values (USTAN and EAM), we re-calculate capital stocks using the perpetual inventory method (PIM), in order to obtain economically meaningful capital series. In doing so, we follow Bachmann and Bayer (2014). To begin with, we compute nominal investment series using the accumulation identity for capital stocks:

$$p_t^I I_{i,k,t} \;=\; K^r_{i,k,t+1} - K^r_{i,k,t} + D^r_{i,k,t},$$

where $K^r_{i,k,t}$ and $D^r_{i,k,t}$ are firm/plant i's reported capital stock and depreciation for capital type k at time t, respectively. Given that capital is reported at historical prices and does not reflect the productive (real) level of capital stock, we apply the PIM to construct economic real capital stock at each type of capital:

$$K_{i,k,1} \;=\; \frac{p_1^I}{p_{base}^I} K^a_{i,k,1}; \quad K_{i,k,t+1} \;=\; K_{i,k,t}(1-\delta_{i,k,t}) + \frac{p_t^I}{p_{base}^I} I_{i,k,t}, \;\; \forall t \;\in\; [0,T]$$

[14] We evaluate the robustness of the imputation procedure, using linear interpolation as an alternative approach. Our empirical findings are robust to this alternative specification.

where $K^a_{i,k,1}$ is the accounting value of the capital stock of type k for the first period we observe the unit, $\frac{p_t}{p_{base}} I_{i,k,t}$ is the real investments in capital k of firm/plant i at time t and $\delta_{i,k,t}$ is the reported depreciation rate of capital k by firm/plant i at time t.[15]

Even though the aforementioned procedure makes sure that values follows a economically meaningful real capital stock series from second period onwards, it is not clear whether the starting (accounting) input of capital at the unit, $K^a_{i,k,t}$, reflects the productive real value. To account and adjust the first period value of capital we use an iterative approach. In specific, we construct a time average factor ϕ_k for each type of capital. It the first iteration step, the adjustment factor takes value of 1 while capital is equal to its balanced sheet value. That is, $K^n_{i,k,t} = \frac{p^I_t}{p^I_{base}} K^a_{i,k,1}$ for $n = 1$. For the subsequent iterations, capital is computed using PIM:

$$K^n_{i,k,t+1} = K^n_{i,k,t}(1 - \delta_{i,k,t}) + \frac{p_t}{p_{base}} I_{i,k,t},$$

while the ajdustment factor is constructed using the ratio between the capital of consecutive iterations

$$\phi^n_k = \frac{1}{NT} \sum_{i,t} \frac{K^n_{i,k,t}}{K^{n-1}_{i,k,t}}.$$

Finally, the capital stock at the first period we observe the unit is adjusted by the factor ϕ^n_k. We apply the procedure iteratively until ϕ_k converges[16]

$$K^n_{i,k,1} = \phi^{n-1}_k K^{n-1}_{i,k,1}.$$

[15] The reported depreciation rate is adjusted such that, on average, it coincides with the economic depreciation rate given by National Accounts. To deflate investment series, we compute an investment good price deflator from each country using the information of gross fixed capital formation at current and constant prices from National Accounts.

[16] We stop whenenever the value of ϕ_k is below 1.1. At each iteration step we drop 0.1% from the bottom and the top of the capital distribution. This cleaning step makes sure to not consider episodes of extraordinary depreciation at the plant, which implies that using reported depreciation rate (adjusted to have the same average value from National Accounts) do not reflect the capital stock given by the PIM.

2.A.2 Second order approximation of unit costs around k^*

For convenience, let us define the relative factor price by $\tilde{R}_t := \frac{R_t}{W_t}$ and (physical) output per worker by

$$f(k_{it}) \;:=\; \frac{Y_{it}}{N_{it}} \;=\; \left[\alpha k_{it}^{\frac{\sigma-1}{\sigma}} + (1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}.$$

Subsequently, marginal costs may be expressed as

$$c_{it} \;=\; W_t \frac{1+\tilde{R}_t k_{it}}{f(k_{it})}$$

and the first derivative of (log) marginal costs with respect to (log) capital intensity,

$$\begin{aligned}
\frac{\partial \log(c_{it})}{\partial \log(k_{it})} &= \frac{\tilde{R}_t k_{it}}{1+\tilde{R}_t k_{it}} - \frac{k_{it} f'(k_{it})}{f(k_{it})} \\
&= \frac{(1-\alpha)\tilde{R}_t k_{it} - \alpha k_{it}^{\frac{\sigma-1}{\sigma}}}{(1+\tilde{R}_t k_{it})(\alpha k_{it}^{\frac{\sigma-1}{\sigma}} + (1-\alpha)A_t^{\frac{\sigma-1}{\sigma}})}
\end{aligned}$$

Let us denote above denominator by $D \equiv (1+\tilde{R}_t k_{it})(\alpha k_{it}^{\frac{\sigma-1}{\sigma}} + (1-\alpha)A_t^{\frac{\sigma-1}{\sigma}})$, and obtain the second derivative as

$$\frac{\partial^2 \log(c_{it})}{\partial \log(k_{it})^2} = \frac{\left[(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t - \frac{\sigma-1}{\sigma}\alpha k_{it}^{-\frac{1}{\sigma}}\right]k_{it}D - \left[(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k_{it} - \alpha k_{it}^{\frac{\sigma-1}{\sigma}}\right]D' k_{it}}{D^2}.$$

The cost-minimizing capital intensity k^* implies $\left.\frac{\partial \log(c_{it})}{\partial \log(k_{it})}\right|_{k_{it}=k^*} = 0$, and the second derivative evaluated at $k_{it} = k^*$, where $(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k_{it}^* = \alpha k_{it}^{*\frac{\sigma-1}{\sigma}}$, is

$$\begin{aligned}
\left.\frac{\partial^2 \log(c_{it})}{\partial \log(k_{it})^2}\right|_{k_{it}=k^*} &= \frac{(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k_{it}^* - \frac{\sigma-1}{\sigma}\alpha k_{it}^{*\frac{\sigma-1}{\sigma}}}{D} \\
&= \frac{(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\frac{1}{\sigma}\tilde{R}_t k_{it}^*}{(1+\tilde{R}_t k^*)((1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k^* + (1-\alpha)A_t^{\frac{\sigma-1}{\sigma}})} \;=\; \frac{1}{\sigma}\frac{\tilde{R}_t k^*}{(1+\tilde{R}_t k^*)^2},
\end{aligned}$$

where the second equation results again from $(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k^* = \alpha k^{*\frac{\sigma-1}{\sigma}}$. The 2nd order Taylor expansion directly follows as

$$\log(c_{it}) - \log(c^*) \;\approx\; \sigma^{-1}\frac{\tilde{R}_t k^*}{(1+\tilde{R}_t k^*)^2}\frac{1}{2}(\log(k_{it}) - \log(k^*))^2.$$

2.A.3 Capital adjustment frictions

Could a friction in capital adjustments explain our empirical findings? Asker et al. (2014) show that capital adjustment frictions can lead to sizeable productivity dispersions and are able to explain international differences in capital productivity dispersions as well. However, they do not provide a decomposition of productivity differences across firms in a persistent and a transitory component and do not report cross-factor correlations. Thus, we explore whether a model with capital adjustment frictions can reproduce our empirical results.

2.A.3.1 Model setup

We assume a one-period production lag as an adjustment friction on labor and, disruption (ϕ^F) and convex cost of capital adjustment costs (ϕ^C). We consider stochastic fluctuations for the decisive relative factor costs W_t/R_t, which follows a Gaussian AR-1 process in logs

$$\omega_t \;=\; \log\left(\frac{W_t}{R_t}\right) \;=\; (1-\rho_\omega)\bar{\omega} + \rho_\omega \omega_{t-1} + \epsilon_t^\omega \qquad \epsilon_t^\omega \;\sim\; \mathcal{N}(0,(1-\rho_\omega^2)\sigma_\omega^2),$$

where $\rho_\omega \in (0,1)$.[17] Similarly, a firm's market size z_{it} evolves as

$$\log z_{it} \;=\; (1-\rho_z)\mu_z + \rho_z \log z_{it-1} + \epsilon_t^z, \qquad \epsilon_t^z \;\sim\; \mathcal{N}(0,(1-\rho_z^2)\sigma_z^2),$$

where $\rho_z \in (0,1)$. As in Section 2.2, we assume a firm knows only current market size z and prices ω, when making the decision to adjust technology for the next period.

[17] For simplicity, we model all movements of factor prices as changes in the real wage rate, keeping interest rates constant.

Analogously to (2.1), we first define the profit maximizing output/employment decision and the corresponding maximal level of expected next period's profits

$$\pi^*(K,z,\omega) \;=\; \max_{N'} \mathbb{E}_{z',\omega'} \left\{ \frac{z'^{\xi}\,[y(K,N')]^{1-\xi}}{1-\xi} - WN' - RK \right\},$$

where output y is given by

$$y(K,N) \;=\; \left[\alpha K^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(AN)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}.$$

Given the disruption cost, the firm chooses between adjusting the stock of capital and staying put every period, the value of which being v^a and v^n, respectively. On the other side, the convex cost renders large capital adjustments less attractive. The firm's dynamic problem is described by the following Bellmann equation

$$\begin{aligned}
v(K,z,\omega) &= \beta \max\left\{v^a(K,z,\omega), v^n(K,z,\omega)\right\}\\
v^a(K,z,\omega) &= \max_{K'}\left\{(1-\phi^F)\pi^*(K',z,\omega) - \phi^C K\left(\frac{K'-K}{K}\right)^2 + \mathbb{E}_{z',\omega'}\left[v(K',z',\omega')\right]\right\}\\
v^n(K,z,\omega) &= \pi^*((1-\delta)K,z,\omega) + \mathbb{E}_{z',\omega'}\left[v((1-\delta)K,z',\omega')\right]
\end{aligned}$$

2.A.3.2 Calibration

We calibrate our model to Germany. A first set of parameters are calibrated outside the model – those parameters that can be observed directly in the data independent of our model: the average relative factor price $\bar{\omega}$. The latter is given by the interest rate r, which we set to 5% as in Section 2.3, the depreciation rate δ, taken as the average implied depreciation rate in the micro data, and the average salary per employee W from the micro data. We calibrate to annual frequency in line with the frequency of the micro data.

Moreover, we create five groups of firms representing the empirical quintiles of the observed markups in the micro data. We set the persistence of shocks to market size z to $\rho_z = 0.9675$ in line with Bachmann and Bayer (2013) that uses the same micro data for Germany. The baseline values of parameters calibrated outside the model is reported in Table 2.9.

Table 2.9. Parameters calibrated outside the model

Interest rate	r	0.05
Depreciation rate	δ	0.09
Avg. real wage (in 1,000 DM)	W	29.2
Demand shifter persistence	ρ_z	0.9675
Demand elasticity	ξ_1	0.19
(5 equally	ξ_2	0.27
large groups)	ξ_3	0.33
	ξ_4	0.38
	ξ_5	0.48

Notes: Real wage W is expressed in Deutsche Mark (1986), which equals 3/4 Euro (2005).

What remains to be calibrated are the parameters of the production function σ, α and A_0, the standard deviation and persistence of relative factor prices σ_ω and ρ_ω, the standard deviation and mean of the demand shifter σ_z and μ_z, as well as the adjustment cost distribution. Of course all parameters are calibrated jointly, but to guide intuition, we link each parameters to those single data moments most informative for them. We calculate all model moments as averages from the corresponding moments of 200 model simulations over 20 periods each (excluding 200 burn-in periods).

To fix μ_z we target average total costs, while σ_z is identified by the volatility of demand shocks σ_z from value added fluctuations.

We calibrate the CES-production function parameters A_0 and α using transformed capital and labor shares as calibration targets – a method suggested by Cantore and Levine (2012).[18] We define

$$\psi_N \;:=\; (1-s)\left(\frac{EX}{N}\right)^{\frac{\sigma-1}{\sigma}} \quad ; \qquad \psi_K \;:=\; s\left(\frac{EX}{K}\right)^{\frac{\sigma-1}{\sigma}} \tag{2.12}$$

where $N = \sum_{i,t} N_{i,t}$, $K = \sum_{i,t} K_{i,t}$ are aggregate labor and capital, respectively, $EX = \sum_{i,t}(W_t N_{it} + R_t K_{it})$ is aggregate total expenditure, $s = \frac{\sum_{i,t} R_t K_{it}}{EX}$ is the aggregate share of capital in total expenditures. Notice that in a frictionless, static version of this

[18] We assume the units of measurement being the number of workers and capital measured in consumption goods expressed in a money value for a baseline year.

model, ψ_N and ψ_K are invariant to relative factor prices and map directly into α and A_0 in (2.6).

To calibrate the factor price process, we let the model match the time series behavior of the aggregate labor share. We opt for the labor share instead of a direct measures of factor prices to control for endogenous reactions of factor prices to shocks to factor augmenting technological change. For our calibration, we first estimate an AR-1 process for the labor share using national statistics data.[19] We use aggregate data here instead of the micro data in order to obtain a longer time series. We then replicate this estimation on simulated data and choose σ_ω and ρ_ω in order to match the empirical labor share process for Germany. We find substantial fluctuations in the German labor share that are fairly persistent, see Table 2.10.

These fluctuations are also closely linked to the substitution elasticity, σ, of the long-run technology. As elaborated in Section 2.4, a regression of the aggregate capital intensity on current factor prices no longer identifies the long-run elasticity of substitution. In a static setup, a regression of the aggregate capital intensity on the contemporaneous relative factor price ω identifies the long-run elasticity of substitution σ, see (2.7). In our frictional dynamic setup, this is no longer the case.

The estimated regression coefficient, $\hat{\sigma}$, will only recover an average correlation, which we refer to as aggregate short-run elasticity of substitution. This will be an average of how current relative factor prices ω_t correlate with the various capital intensities, weighted by their share in the economy.

Yet, such measure of the short-run aggregate elasticity – the regression coefficient of aggregate capital intensity, $\log(\sum_i K_{it}) - \log(\sum_i N_{it})$, on relative factor prices ω_t – is informative for the long-run elasticity.

We therefore calibrate σ by matching an aggregate short-run substitution elasticity of 0.75 which is mid-range of the numbers summarized in Chirinko (2008). We provide extensive robustness checks with respect to this calibration target.

Finally, to calibrate fixed and convex adjustment costs, we target the skewness and kurtosis of gross investment rates for the German USTAN data as in Bachmann and Bayer (2013).

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[19] Given there is no available information on the labor share in manufacturing at Indonesia from National Statistics, we opt to construct aggregate labor share using the micro data.

Table 2.10. Parameters calibrated within the dynamic model

Calibration targets		Data	Model
Avg. factor expenditures (in 1,000,000 DM)		7.54	6.31
log(VA) std.		1.24	1.15
Transformed capital share, ψ_K		0.17	0.16
Transformed labor share, ψ_N		210.90	218.96
Aggr. labor share std. (in %)		3.30	5.13
Aggr. labor share persistence (in %)		88.1	87.6
Aggr. (short-run) substitution elasticity		0.75	0.75
Skewness gross investment rate		2.19	2.35
Kurtosis gross investment rate		20.04	18.91
Calibrated model parameters			
CES substitution elasticity	σ		2.13
CES capital weight (in %)	α		16.80
CES labor productivity (in 1,000 DM)	A_0		33.70
Relative factor price std. (in %)	σ_ω		0.78
Relative factor price persistence (in %)	ρ_ω		0.30
Demand shifter std.	σ_z		1.20
Demand shifter mean (in 1,000,000 DM)	μ_z		7.60
Disruption cost	ϕ^F		0.18
Quadratic cost	ϕ^C		0.06

Notes: Calibration targets K/N and $WN + RK$, and parameters μ_z and A_0 are expressed in Deutsche Mark (1986), which equals 3/4 Euro (2005). The model is simulated for a set of 200 economies with each 2,000 plants and 20 years. log(VA) std.: Cross-Sectional standard deviation of log of value added of firms.

2.A.3.3 Results

Table 2.11 presents the cross-sectional standard deviations from the simulated model. The cross sectional dispersions are obtained as averages over 200 sets of economies where we simulate 2,000 plants for 20 years.

As shown in as in Asker et al. (2014), capital adjustment frictions can explain the overall dispersions in capital productivities well, and in our model account for 88% of the total empirical variance.

However, the model generates long-lived differences in capital productivity that are too small compared to the data (55% of the variance) and short-lived differences that are too large (330% of the variance). In addition, the correlations between labor

Table 2.11. Transitory and persistent components of factor productivities, markups, and capital intensities in the capital adjustment model

	Transitory Component			Persistent Component		
	std($\hat{\alpha}_{it}^L$)	std($\hat{\alpha}_{it}^K$)	$\rho(\hat{\alpha}_{it}^L, \hat{\alpha}_{it}^K)$	std($\bar{\alpha}_{it}^L$)	std($\bar{\alpha}_{it}^K$)	$\rho(\bar{\alpha}_{it}^L, \bar{\alpha}_{it}^K)$
Data	0.07	0.12	0.35	0.23	0.46	-0.21
Baseline	0.02	0.25	-0.92	0.15	0.37	0.40
	std($\hat{mc}_{it}$)	std($\hat{\kappa}_{it}^K$)	$\rho(\hat{mc}_{it}^L, \hat{\kappa}_{it}^K)$	std($\bar{mc}_{it}^L$)	std($\bar{\kappa}_{it}^K$)	$\rho(\bar{mc}_{it}^L, \bar{\kappa}_{it}^K)$
Data	0.06	0.11	-0.16	0.17	0.55	0.06
Baseline	0.03	0.27	-0.82	0.15	0.34	-0.38

Notes: Cross-sectional standard-deviations (std) and correlation (ρ) of transitory and persistent components of labor- and capital productivity, α_{it}^L and α_{it}^K as in (2.9), and capital intensities, κ_{it}, and markups, mc_{it}, as defined in (2.10) and (2.11). All second moments are computed as averages over 200 sets of economies simulated with 2,000 plants and for 20 years.

and capital productivity show the wrong signs when split into transitory and persistent components. This mechanically implies transitory differences in capital intensity making up a large part (40%) of the model's total capital-intensity variance. Again this stands in sharp contrast to the data. Table 2.12 shows that these patterns are highly robust to the model calibration.

The reason for this lies in the basic mechanics of any model with different degrees of flexibility in labor and capital. When one factor is more flexible than the other, a firm will use the more flexible factor strongly to accommodate shocks to its optimal scale. For example, as demand z in the capital-adjustment model goes up, the firm wants to raise production and will do so by hiring more labor on impact and only subsequently adjust capital. Therefore, capital intensity drops on impact and recovers thereafter.

This shows how idiosyncratic shocks to optimal scale translate directly into transitory idiosyncratic movements in capital intensity in any model that features different degrees of flexibility of labor and capital. As discussed before, our calibrated model indeed implies too large transitory differences in capital intensity relative to persistent ones.

Table 2.12. Alternative calibrations of capital adjustment costs model, Germany

	Transitory Component			Persistent Component		
	std($\hat{\alpha}_{it}^L$)	std($\hat{\alpha}_{it}^K$)	$\rho(\hat{\alpha}_{it}^L, \hat{\alpha}_{it}^K)$	std($\bar{\alpha}_{it}^L$)	std($\bar{\alpha}_{it}^K$)	$\rho(\bar{\alpha}_{it}^L, \bar{\alpha}_{it}^K)$
Data	0.07	0.12	0.35	0.23	0.46	-0.21
Baseline	0.02	0.25	-0.92	0.15	0.37	0.40
D.log(VA)	0.01	0.14	-0.91	0.15	0.23	0.74
Ela. 0.5	0.01	0.22	-0.86	0.14	0.41	0.62
Ela. 1.0	0.03	0.29	-0.92	0.15	0.41	0.30
50% σ_ω	0.02	0.31	-0.94	0.15	0.38	0.34
	std($\hat{mc}_{it}$)	std($\hat{\kappa}_{it}^K$)	$\rho(\hat{mc}_{it}^L, \hat{\kappa}_{it}^K)$	std($\bar{mc}_{it}^L$)	std($\bar{\kappa}_{it}^K$)	$\rho(\bar{mc}_{it}^L, \bar{\kappa}_{it}^K)$
Data	0.06	0.11	-0.16	0.17	0.55	0.06
Baseline	0.03	0.27	-0.82	0.15	0.34	-0.38
D.log(VA)	0.02	0.15	-0.93	0.15	0.16	-0.31
Ela. 0.5	0.02	0.23	-0.85	0.16	0.34	-0.59
Ela. 1.0	0.03	0.32	-0.79	0.15	0.39	-0.36
50% σ_ω	0.04	0.33	-0.88	0.15	0.35	-0.38

Notes: In the third row, D.log(VA) is as the baseline model but targets the cross sectional dispersion of first differences of log value added instead of the dispersion in log value added. Ela. 0.5 and 1.0 refer to changing the target aggregate short-run substitution elasticity to 0.5 and 1.0, respectively. 50% σ_ω recalibrates the model with a 50% smaller dispersion in relative factor dispersion. See notes of Table 2.11 for further explanation.

3

Do Plants Freeze Upon Uncertainty Shocks?

Joint with Matthias Meier

3.1 Introduction

It has been well documented that uncertainty is high during recessions. However, there is no consensus whether changes in uncertainty can actually lead to sizable business cycle fluctuations. The underlying effects differ substantially depending on the transmissions mechanism through which it affects the economy.

In this paper we assess through which channels uncertainty shocks impact employment by studying its effects on the creation and destruction of jobs. To guide our empirical analysis, we consider a dynamic problem of the plant facing frictions in factor adjustments, price rigidities, or financial frictions.

The qualitative response of job flows to an uncertainty shock depends on the channel by which it affects the economy. Under costly labor adjustments, an unexpected increase in uncertainty causes plants to temporarily stop their employment adjustments and, consequently, there are less jobs created and destroyed. Analogously, given costly capital adjustments, heightened uncertainty leads to higher inactivity of investments adjustments, which implies a decline of capital and labor demand due to complementarity in the production. Further, under staggered price-setting, plants respond to an uncertainty shock by setting a higher price relative, as the profit function is asymmetric in the price. As a result, more jobs are destroyed and less jobs created. Finally, under financial frictions, an increase of uncertainty leads to higher borrowing costs as default is more likely. Therefore, as the price for the bond declines, and establishments reduce their exposure to default, there is less creation and more destruction of jobs.

These, however, are not the only implications. The quantitative effect from an uncertainty shock depends on the size of these frictions. As higher the degree of factor adjustment frictions, price flexibility, and vulnerability to financial conditions, stronger the resulting responses from an uncertainty shock.

To explore whether these implications are borne out empirically, we estimate the effect of uncertainty shocks on industry-level job flows in the United States. We construct a new dataset which consists of quarterly job flows at the 4-digit Standard Industrial Classification (SIC) level based on the period 1972-2013. Following the econometric approach from Davis and Haltiwanger (2001),[1] we consider a sectoral VAR which contains common aggregate variables - stock market level, uncertainty, and aggregate job flows - and industry-level job flows. The system is specified such that the uncertainty shock is common across sectors, while the estimated response functions differs across sectors.

An unexpected increase in uncertainty leads to more jobs destroyed and less jobs created for more than 80% of the industries. This finding suggests that plants do not freeze employment adjustments given this shock.

In order to assess which channels are important for explaining the resulting effects at the industry-level, we regress the cumulative responses from an uncertainty shock on variables reflecting factor adjustment frictions, price rigidities, and financial frictions at the industry. We do not find evidence of factor adjustment frictions or price rigidities as channels through which uncertainty affects job flows. On the contrary, financial frictions surges as an important channel. Industries associated to be more vulnerable to financial conditions report 75% stronger job flow responses than the least vulnerable industries.

This study is related to a growing literature that analyzes the macroeconomic effects of uncertainty shocks. The literature discusses several mechanisms through

[1] Davis and Haltiwanger (2001) exploits industry-level job flows responses to oil shocks to identify sectoral characteristics which are related to the effects at the industry-level.

which uncertainty affects economic activity.[2] In this paper we assess these mechanisms within a common empirical framework. Our analysis is particularly related to those studies that evaluates, empirically, the effects of uncertainty shocks on labor markets. The current available evidence concentrates on the effects at unemployment rate (Leduc and Liu, 2014), job finding rate (Guglielminetti, 2013), and separation rate in connection with job finding rate (Riegler, 2014). While our empirical findings are in line with their results, we differ in that we consider the effects of uncertainty shocks on the disaggregated responses at the industry-level, which allows us to investigate which channels matter for explaining the effects of uncertainty shocks in the economy.

The structure of the paper continues as follows. Section 3.2 analyzes the theoretical effect of uncertainty shocks on aggregate job flows based on a model with factor adjustment costs, price rigidities, or financial frictions. Section 4.2.2 describes the data used in this study, and it is followed by our estimation strategy in Section 3.3. Section 3.5 makes use of the theoretical implications arrived in Section 3.2, and empirically assess the importance of each friction for explaining the resulting effects of uncertainty shocks. Finally, Section 3.6 concludes.

3.2 Theoretical Background:

We study a dynamic problem of the plant facing either factor adjustment frictions, price rigidities, or financial frictions. For each case, we aim to understand the implications of uncertainty shocks on the creation and destruction of jobs. Following Davis and Haltiwanger (1992), we define gross job creation as the total employment gains from expanding and new establishments in an industry. In a similar manner, we define gross job destruction as the total employment losses from shrinking and closing establishments in an industry.

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[2] See, for example, Bloom (2009), Bachmann and Bayer (2013) and Bloom et al. (2014) on factor adjustment costs, Schaal (2012), Leduc and Liu (2014) and Riegler (2014) on labor search frictions, Alfaro et al. (2016),Christiano et al. (2010), Arellano et al. (2012), Gilchrist et al. (2013), and Dyrda (2015) on financial frictions, and Bundick and Basu (2014), Born and Pfeifer (2016), Fernandez-Villaverde et al. (2015) and Vavra (2014) on price rigidities.

We consider an economy with a unit mass of plants that produce output y_{it} based on a constant returns to scale production function, determined by capital and labor

$$y_{it} = L_{it}^{\alpha} K_{it}^{1-\alpha}.$$

Plants face monopolistic competition and choose its optimal price subject to the demand function

$$y_{it} = \left(\frac{z_{it} P_t}{p_{it}}\right)^{\epsilon} Y_t,$$

where z_{it} is the stochastic demand for the product i, Y_t is the aggregate demand, and P_t is the aggregate price. Consequently, revenues are determined as

$$R_{it} = P_t Y_t^{-1/\epsilon} z_{it} L_{it}^{\alpha\mu} K_{it}^{(1-\alpha)\mu}, \tag{3.1}$$

where $\mu \equiv \frac{\epsilon-1}{\epsilon}$.

We assume that idiosyncratic demand z follows a log-normal AR(1) process

$$\log(z_{it}) = \mu_z + \rho \log(z_{it-1}) + \sigma_{t-1}\epsilon_{it},$$

where $\epsilon_{it} \sim N(0,1)$ are independent across units, $\mu_z = -\sigma_{t-1}/2$, and σ_t moves according to a two state Markov chain, allowing for high and low uncertainty states

$$\sigma_t \in \{\sigma_L, \sigma_H\} \text{ where } P(\sigma_{t+1} = \sigma_r | \sigma_t = \sigma_m) = \pi_{mr}^{\sigma}$$

In the following sections we extend the model with micro-level frictions which shape the response of aggregate job flows from uncertainty shocks.

3.2.1 Labor adjustment frictions

The distribution of net employment growth at the establishment-level exhibits excess kurtosis. This suggests that net employment changes are lumpy and discontinuous, and advocates for the presence of non-convex labor adjustment costs at the plant-level.[3] For sufficiently low realizations of demand, establishments lower their labor

[3] See, for example, Caballero et al. (1997) and Davis et al. (1998).

units. Akin, for sufficiently high realizations of demand, establishments increase their labor units. However, for intermediate values of productivity, not adjusting is more valuable.

Given an uncertainty shock, the option value of not adjusting increases.[4] As labor adjustments are costly, a larger share of plants postpone adjustments in order to avoid incurring costs which are likely to be reversed given higher volatility of economic conditions. Therefore, an unexpected rise of uncertainty leads to a decline in aggregate job creation and job destruction.[5]

For the purpose of understanding the implications of uncertainty shocks under different degrees of labor frictions we consider a dynamic problem of the plant where capital stock is freely adjustable and rented at a cost $r + \delta$, while employment adjustments are subject to non-convex adjustment costs $C_L(L, L')$ and pay for a unit of labor service w. The problem of the plant is given by

$$V(z, L, \sigma) = \max_{L',K} \left\{ R(z, L', K) - wL' - (r + \delta)K - C_L(z, L, L') + \beta E\Big[V(z', L', \sigma') \Big] \right\},$$

where $C_L(L, L')$ includes partial irreversibility costs C_L^p and fixed costs C_L^f, such that[6]

$$C_L(L, L') = \begin{cases} C_L^f + C_L^p \mid L' - L \mid & \text{if } L' \neq L, \\ 0 \text{ if } L' = L. \end{cases}$$

[4] The option value of not adjusting employment surges when we consider a model with non-convex labor adjustment costs. On the contrary, if we consider convex labor adjustment costs, there is no option value of remaining inactive, see Bloom (2009).

[5] In order to arrive to this conclusion, we are implicitly assuming that adjustment costs are born out on net employment changes as in Cooper and Willis (2009). That is, under the presence of exogenous quits, labor adjustment costs would be zero if plants adjust employment to offset quits. The literature alternatively considered exogenous quits in combination with non-convex adjustment costs at gross employment changes. However, the combination of exogenous labor attrition and sufficiently high adjustment costs at gross employment changes implies a negative median at the distribution of net employment growth, while empirically, is commonly non-negative, see Davis and Haltiwanger (1992).

[6] The fixed costs of labor adjustments are expressed in proportion to profits.

3.2.2 Capital adjustment frictions

As employment, the distribution of gross investment rate exhibits excess kurtosis and negative skewness, which suggests that plants face non-convex capital adjustment costs. This commonly leads to a region of inactivity of investment adjustments.

An unexpected rise of uncertainty increases the region of inactivity.[7] Given costly capital adjustments, the option value of not investing increases. Assuming that plants accumulate capital stock, which declines by depreciation rate if not investing, net capital decreases at the inactive plants, and labor demand falls indirectly.[8]

This results into less jobs created, as plants who normally invest under low uncertainty levels, do not do so under high uncertainty levels. The effect on job destruction is unclear. First, there is a downward effect on job destruction from plants that would sell their capital stock under low uncertainty levels, while they do not do so under high uncertainty. On the contrary, there is an upward effect on job destruction given higher inactivity of investment adjustments. As a result, it depends on the relative strengths of these two forces.

In order to understand the effect of uncertainty on aggregate job flows under different degrees of capital adjustment costs, we study a dynamic problem of the plant subject to non-convex capital adjustment costs $C_K(I)$ and where labor is freely adjustable, paying for its labor services w

$$V(z,K,\sigma) = \max_{L',I}\left\{R(z,L',K(1-\delta)+I) - wL' - C_K(I) + \beta E\Big[V(z',K(1-\delta)+I,\sigma')\Big]\right\}$$

where $C_K(I)$ consists of partial irreversibility costs C_K^p and fixed costs C_K^f such that[9]

$$C_K(I) = \begin{cases} C_K^f + I^+ - (1-C_K^p)I^- \text{ if } I \neq 0, \\ 0 \text{ if } I = 0, \end{cases}$$

---

[7] Similar to Section 3.2.1, this conclusion does not hold if we would only consider convex capital adjustment costs, as there is no option value of remaining inactive.

[8] Using Equation 3.1, the change in labor demand as a function of the change in capital is given by $\log(L_{it}) \approx -(1-\alpha)\Delta\log(K_{it})/\alpha$.

[9] The fixed costs of capital adjustments are expressed in proportion to profits.

and $I^+(I^-)$ are the absolute values of positive (negative) gross investments. Given the functional form of capital adjustment costs, the resale value of capital is commonly lower than the purchased value. In this regard, Ramey and Shapiro (2001) exploits machinery purchases and sales from the aerospace industry and find that capital sells are commonly subject to a large discount.

3.2.3 Price rigidities

In an economy with monopolistic competition and staggered prices, plants respond to an uncertainty shock by setting a higher price relative to normal uncertainty level. The combination of more likely tail events and the profit function being asymmetric in the price (it is costlier to set a lower price relative to the competition compared to setting higher relative price) leads to this upward pricing policy. Consequently, there are less jobs created and more jobs destroyed.[10]

In order to explain the effects from uncertainty shocks under different degrees of price rigidities, we consider a problem of the plant that faces price adjustments frictions a la Calvo (1983). Furthermore, we allow for fluctuations in the aggregate price, and assume it follows a log-normal AR(1) process

$$\log(P_t) \ = \ \mu_P + \rho \log(P_{t-1}) + \sigma \epsilon_t^P,$$

where $\epsilon_t^P \sim N(0,1)$ are independent across time, $\mu_P = -\sigma_{t-1}/2$.[11]

We restrict plants to set prices before the realization of shocks from the current period, while labor and capital are freely adjustable, paying for its services the wage rate w and user cost $r + \delta$, respectively. The dynamic problem of the plant, subject

[10] These implications arise if we assume Rotemberg or Calvo price adjustment costs and prices are set before shocks realize, see Fernandez-Villaverde et al. (2015) and Born and Pfeifer (2016). On the contrary, if we consider a model with fixed costs of price adjustments and time-varying uncertainty as in Vavra (2014), an uncertainty shock increases the frequency and volatility of price changes, resulting into more jobs created and destroyed.

[11] In this model, time-varying uncertainty about idiosyncratic demand does not affect plants' price policy, while uncertainty about the aggregate price it does. Therefore, we further include time-varying uncertainty about the aggregate price in this particular model.

to price rigidity, after maximizing with respect to labor and capital, is determined by

$$V(z,p,P,\sigma) \;=\; E\Big[\theta \max_{p'} \tilde{V}(z',p',P',\sigma') + (1-\theta)\tilde{V}(z',p,P',\sigma')\Big]$$

where θ denotes the price adjustment probability, and $\tilde{V}$ is given by

$$\tilde{V}(z,p,P,\sigma) \;\equiv\; \left[\frac{p}{P} - \left(\frac{w}{\alpha}\right)^{\alpha}\left(\frac{r+\delta}{1-\alpha}\right)^{1-\alpha}\right]\left(\frac{zP}{p}\right)^{\epsilon} + \beta V(z,p,P,\sigma).$$

3.2.4 Financial frictions

Fluctuations in uncertainty may, alternatively, impact the economy through financial frictions. In the following, we consider a dynamic problem of the plant which highlights the role of liquidity given incomplete financial markets and fluctuations in uncertainty. This framework allows us to arrive at implications based on the degree of vulnerability to financial frictions. The model described below is in spirit of the model by Arellano et al. (2012).

To investigate the effects of financial frictions, we assume that plants choose next period debt level and labor units in the current period. Compared to the previous setups, we abstract from capital in the economy, and assume that plants are subject to fixed operating costs F.[12]

The plant may finance its expenditures by issuing a defaultable one-period bond. The debt contract pays b' units conditional on not defaulting, and provides qb' in return. We consider a simplified financing cost structure, where plants are unable to finance with equity nor to have negative dividends:

$$d \;=\; R(z,L) - wL - b + q(L',b',z_t,\sigma_t)b' - F \;\geq\; 0,$$

such that whenever this condition does not hold, the plant defaults. In this problem, default occurs because plants do not have enough liquid funds to manage the low demand level or high indebtedness.

[12] We assume the production to depend only on labor for model tractability reasons. Furthermore, we include fixed operating costs in order to generate default in equilibrium. The implications of this model would still hold if production is determined by labor and capital, and plants make decisions on the production factors before demand realizes.

Based on this environment, the value function of a continuing establishment is given by

$$V(z,L,b,\sigma) \;=\; \max_{b',L',d} d \,+\, \nu\beta E[V(z',L',b',\sigma')],$$

where an establishment exogenously exits the market with probability $1-\nu$ every period.[13]

To derive the price of the bond, we assume that establishments may sign a one period loan contract with a perfectly competitive financial intermediary. If the plant saves ($b<0$), it does so at the risk free rate. On the contrary, if the plant accumulates debt, it may default $\psi(z,L,b,\sigma)=1$, and the lender may recover part of what has been lent by taking possession of the plant, starting with zero debt level, at a cost ξ.[14] Therefore, the price of the bond is determined as

$$q(L',b'|z,\sigma) \;=\; \begin{cases} \beta E\left[\psi(z',L',b',\sigma') + \frac{(1-\psi(z',L',b',\sigma'))}{b'} \min\left\{b', \max\left\{\bar{V}(z',L',0,\sigma'),0\right\}\right\}\right] \text{ if } b' \;>\; 0, \\ \beta \text{ if } b' \;\leq\; 0, \end{cases}$$

where $\bar{V}(z',L',0,\sigma') \equiv V(z',L',0,\sigma') - \xi$. In the next section we evaluate the response of job flows from an uncertainty shock at different costs ξ. A lower recovery value implies higher vulnerability to financial frictions and lower bond price q. The parameter ξ can be thought of as a cost for processing bankruptcy, but also determines how much from plants' value can be collateralized. It is related to the costly verification problem in Townsend (1979) and Bernanke and Gertler (1989). We differ in that shocks in our model are persistent and observable by the lender, while in the other setup, shocks are i.i.d. and unobservable by the lender.

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[13] The assumption of exogenous exit rate motivates the use of debt by plants, see, for example, Bernanke et al. (1999) and Gertler and Kiyotaki (2010). We assume that whenever a plant defaults or exogenously exit, it is replaced by identical plant in the next period with zero debt level.

[14] We express ξ proportional to optimal revenues in the steady state. As in Gilchrist et al. (2013), the exogenous exit rate is not included in the loan price. We are implicitly assuming that plants make their payment decisions before the exit shock realizes.

3.2.5 The theoretical effects from uncertainty shocks

To solve the dynamic problems, we calibrate the parameters at quarterly frequency, in line with the frequency of our empirical analysis. We consider standard assumptions for α, ϵ, δ, and r. As Cooper and Willis (2009), the wage rate is specified such that steady state employment at the plant consists of 600 workers.[15] The demand and uncertainty process are based on the estimated processes from Bloom et al. (2014).[16] Finally, following Gilchrist et al. (2013), we parametrize the exogenous exit rate based on establishment entry and exit tabulations from the Business Employment Dynamics, and the fixed operation costs based on the ratio of general expenses to sales from Compustat data.[17]

After solving the dynamic problems, we independently simulate 5000 economies with 1000 plants, each of 80-quarter length. At each economy, the model is hit with an uncertainty shock at the fifth quarter.[18] In order to calculate the response of aggregate job flows to an uncertainty shock, we compute aggregate job flows for each period and average across all economies.

Figure 3.1 shows the impact of an uncertainty shock under different degrees of frictions. As higher the costs to adjust labor, larger the share of plants which remain inactive in a given period, but also higher the incentives to postpone adjustments until uncertainty returns back to normal levels. Therefore, as larger the costs to adjust employment, stronger the decline in aggregate job flows. Similarly, under the capital frictions, as higher the costs to adjust capital, larger the incentives to postpone investments and stronger the decline in the creation of jobs. However, as argued in Section 3.2.2, the effect of uncertainty shocks on job destruction is unclear and depends on the size of capital adjustment costs.

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[15] This number corresponds to the average workers at a US manufacturing plant based on the Longitudinal Research Database, see Caballero et al. (1997).

[16] Bloom et al. (2014) calibrates a dynamic stochastic general equilibrium model, where firms face factor adjustment frictions, to quantify the macroeconomic implications of time varying uncertainty.

[17] Based on firm-level data from Compustat, the median ratio of sales, general, and administrative expenses to sales is 22%. As Gilchrist et al. (2013), we assume that 50% of those expenditures represent fixed costs of operations.

[18] The first 50 simulated economies are discarded such that results are independent of the assumed initial conditions.

Table 3.1. Parametrization

Parameter	Value	Explanation
α	0.65	Labor share in the economy
ϵ	4	Markup of 33%
β	0.99	Discount factor at quarterly frequency
δ	2.6%	Annual capital depreciation of 10%
r	1.01%	Annual risk free interest rate of 4%
ρ	0.95	Serial correlation process
σ_L	0.051	Baseline uncertainty level
σ^H	4 x σ	High uncertainty is four times the baseline level
$\pi^{\sigma}_{L,H}$	0.03	Probability from low to high uncertainty
$\pi^{\sigma}_{H,H}$	0.92	Probability of remaining at high uncertainty state
All models except financial frictions		
w	0.113	Employment at the plant consists of 600 workers in the steady state
Model with financial frictions		
w	0.07	Employment at the plant consists of 600 workers in the steady state
ν	0.95	Survival probability
F	8	Fixed costs of operations. Represents 11% of optimal revenues in the steady state

Notes: The demand and uncertainty process are set to the same process as Bloom et al. (2014). As in the model with financial frictions (Section 3.2.4) we do not consider capital in the economy, we set $w = 0.07$ such that optimal employment at the plant is 600 workers in the steady state.

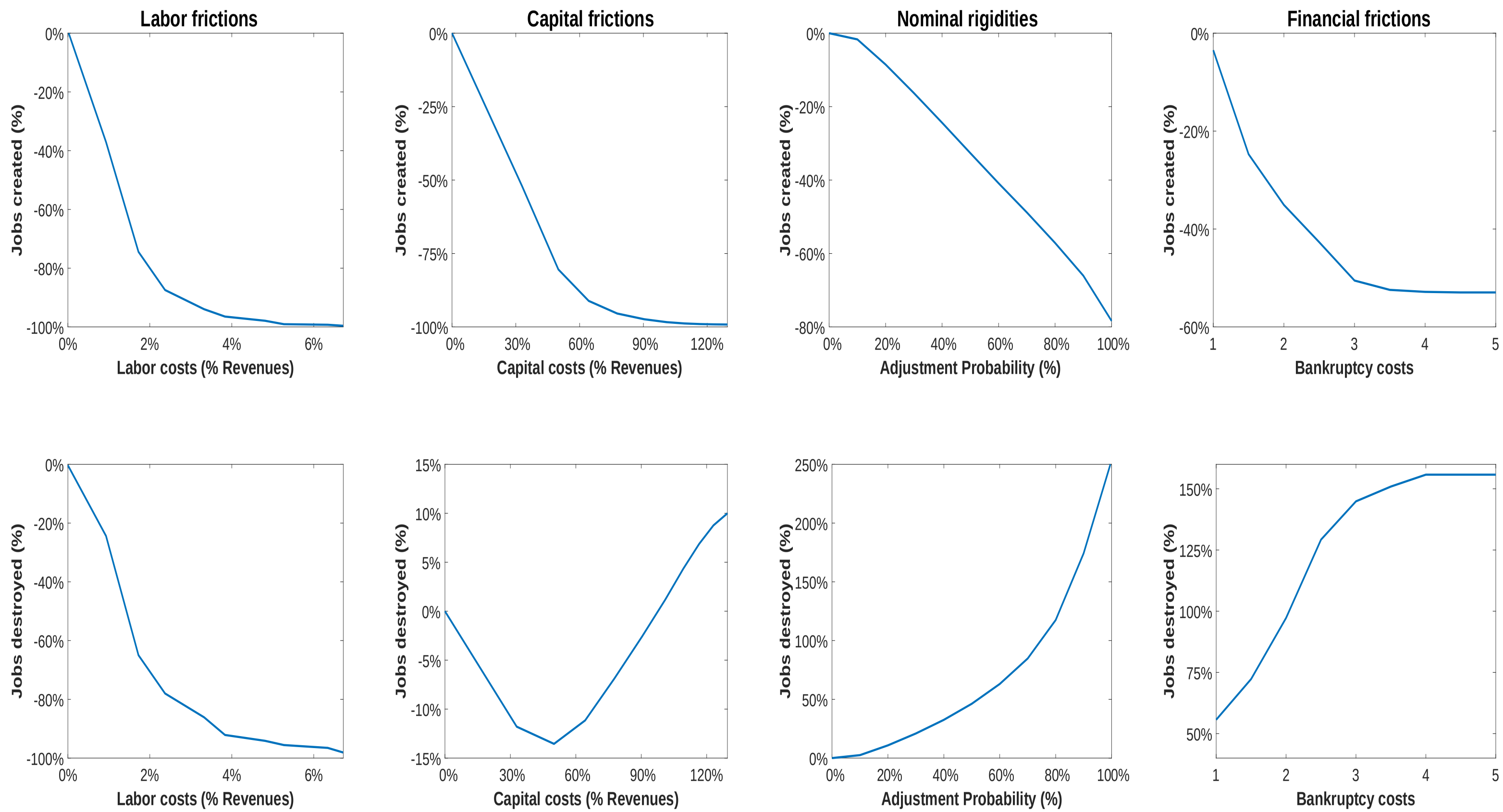
Under price rigidity, the response of job flows from uncertainty shocks are stronger as lower is the underlying price rigidity in the economy. Those establishments which able to adjust their prices adopt an upward price policy in response to the shock, while the remaining establishments keep the same price level.

Finally, in an economy with financial frictions, heightened uncertainty increases the probability of default given that tail shocks are more likely. Therefore, the bond price declines, which leads to more jobs destroyed and less jobs created. Furthermore, as higher is the vulnerability to financial frictions (higher ξ), lower is the recovery value under default, resulting into stronger decline of the bond price from an uncertainty shock. As a result, the effects on job flows are larger as higher is the vulnerability to financial frictions.

Our model with financial frictions stress the importance of liquidity. Alternatively, we may consider an economy where borrowing is subject to collateral constraints. An increase of uncertainty makes default more likely, which commonly leads lenders to charge a higher risk premium and raise collateral requirements. Consequently, establishments reduce the demand for production factors. Importantly, plants with lower creditworthiness or collateral value, are disproportionally affected from the shock. As highlighted by Bernanke et al. (1996), given that these businesses are more exposed to agency and moral hazard problems, the flow of credit declines by relatively more.[19]

[19] In a related framework, Dyrda (2015) considers a model where firms face borrowing constraints and fluctuations in uncertainty. In his setup, young firms are relatively more constrained in borrowing. An uncertainty shock leads to tighter borrowing constraints, and affects disproportionally more young firms.

Figure 3.1. Theoretical effects from an uncertainty shock



Notes: The figure shows, for different size of labor frictions, capital frictions, price rigidity, and financial vulnerability, the percentage change of aggregate jobs flows in the first quarter after an uncertainty shock. Labor (Capital) costs (% Revenues) denote the average costs, as a share of revenues, incurred by those plants who adjust employment (capital) at the first simulated quarter. Bankruptcy costs are proportional to optimal revenues in the steady state. The model with labor frictions is solved for $C_L^f \in \{0, 0.0005, ..., 0.05\}$ and $C_L^p \in \{0, 0.1, .., 1\}$, while for capital frictions $C_K^f \in \{0, 0.0005, ..., 0.05\}$ and $C_K^p \in \{0, 0.1, .., 1\}$, for price rigidity $\theta \in \{0, 0.1, .., 1\}$, and for financial frictions $\xi \in \{1, 0.5, ..., 5\}$.

3.3 Estimation strategy

Based on these findings, we explore, empirically, the effects of uncertainty shocks on job flows. We consider a structural vector autoregressive model that contains common and industry specific variables:

$$B^{-1}Y_t = B_0\tau + B(L)Y_{t-1} + \zeta_t, \tag{3.2}$$

where Y_t is a vector of variables containing the log of S&P 500 stock market index, uncertainty, log of aggregate manufacturing job flows and the log of sectoral job flows. The matrix $B(L)$ is the p^{th} order matrix polynomial with lag operator L, τ is a vector of constants, B^{-1} is the contemporaneous impact matrix and ζ is the vector of structural shocks. We are interested about recovering impulse responses of sectoral job flows given a structural shock to uncertainty. Yet, we need to impose restrictions to obtain structural shocks from the reduced form VAR

$$Y_t = A_0\tau + A(L)Y_{t-1} + \omega_t, \tag{3.3}$$

where $\omega_t \equiv B\zeta_t$ is the vector of reduced form residuals.

Following the econometric approach from Davis and Haltiwanger (2001), we partially identify the structural response functions by placing restrictions on $A(L)$ and B. The restrictions on the former are given by

$$a_{i,jc}(l) = a_{i,jd} = 0, \ \forall\, l \text{ and } i = s, u, ajc, ajd$$

where $\{s, u, ajc, ajd, jc, jd\}$ denote indicator for the stock market index, uncertainty, aggregate job flows, and industry-level job flows, respectively, and $a_{i,k}(l)$ denotes the $\{ik\}$ element at lag l of $A(L)$. These restrictions allows us to make sure the uncertainty shock is identical across industries.

Furthermore, we impose restrictions on B. We assume that stock market level is not contemporaneously affected by an uncertainty shock nor shocks to job flows. Including the stock market level first in the recursive ordering ensures that uncertainty shocks are orthogonal to first moment shocks. In addition, we do not allow shocks to job flows to contemporaneously affect uncertainty. Finally, we restrict shocks to industry-level job flows to not contemporaneously affect aggregate job flows.

Since we are only interested about identifying structural innovations to uncertainty, we do not need to fully determine the contemporaneous covariance matrix. The block recursive nature of the system suffices to identify the responses from this structural innovation.[20]

Based on these assumptions, we estimate impulse responses from uncertainty shocks using local projections. Compared to the estimation of impulse responses directly from the VAR system, local projections is more robust to misspecification of the unknown data generation process. It makes use of single coefficient matrices instead of relying on nonlinear functions of the estimates of the VAR slope parameters (see Jorda (2005) and Kilian and Kim (2009)). Consider the projection of Y_{t+h} onto the linear space $(Y_{t-1}, Y_{t-2}, ..., Y_{t-p})'$:

$$Y_{t+h} \;=\; \mu^h + \sum_{l=1}^{P} M_l^{h+1} Y_{t-1-l} + u_{t+h}, \tag{3.4}$$

where u_{t+h} is the error term which we assume to have zero mean and strictly positive variance. The resulting impulse response at horizon h from a structural shock to the i^{th} element in Y_t, $IR(h,i)$, is given by

$$IR(h,i) \;=\; M_1^h c_i \tag{3.5}$$

where c_i corresponds to the i^{th} column of matrix B.

3.4 Data

3.4.1 Job Flows

We consider industry-level job flows in the United States from two sources. First, for the period of 1972-1998, we exploit the series built by Davis et al. (1998), which provides information at the 4-digit SIC level for 456 manufacturing industries us-

[20] We do not attempt to achieve identification within aggregate manufacturing job flows and within sectoral job creation and destruction.

ing the Longitudinal Research Database (LRD).[21] We further extend the series until 2013 using the Quarterly Workforce Indicator (QWI), available through the United States Bureau of the Census (2015). The QWI measures worker and job flows disaggregated at the 4-digit NAICS level.[22] As participation increased over the period, we consider only those states who started reporting information earlier than 2000Q2. The selected sample constitutes 90% manufacturing employment in United States. We use X-13 ARIMA to remove the seasonal component from the series.[23]

Figure 3.2 shows the aggregate time series of manufacturing employment based on our sample, relative to tabulations from the Bureau of Labor Statistics. Given the limited amount of states in the second sample, our estimated aggregate employment is lower relative to the aggregate statistics. Yet, the correlation between these series is 98%. We refer the reader to Appendix 3.A.3 for additional details about this data.

3.4.2 Uncertainty

As uncertainty is not directly observable, the literature relies primarily on financial and survey indicators to construct proxies. In this study, we consider the variables constructed by Ludvigson et al. (2015) and Jurado et al. (2015). The authors stress the importance of distinguishing between variability and predictability of economic indicators. Taking this into account, they construct macroeconomic uncertainty as the common factor of uncertainty related to real economic activity, prices, bond and stock market indexes, among others. Similarly, financial uncertainty is based on the uncertainty about financial variables, such as credit spreads, valuation ratios, risk factors, among others. Our baseline analysis is based on the quarterly averaged

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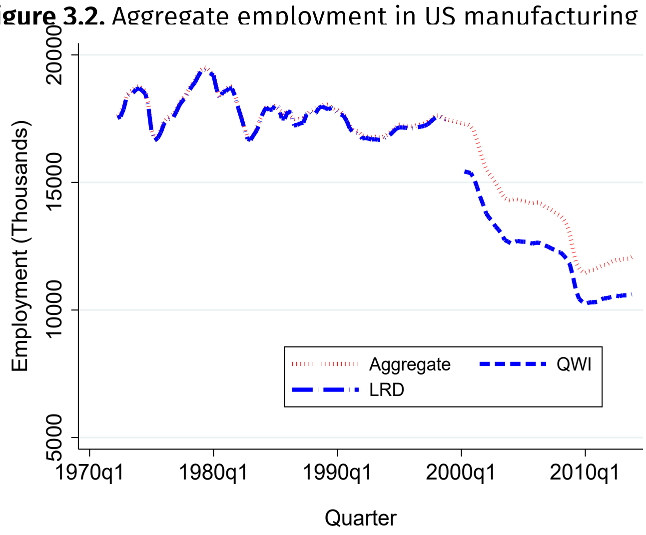
[21] The LRD collects employment information from all US manufacturing establishments with at least five or more employees and accounts for more than 99% of manufacturing employment in the country.

[22] The QWI is based on the Longitudinal Employer-Household Dynamics (LEHD). The LEHD consists of linked employer-employee data covering over 95% of US private sector jobs. It considers employer's state-specific UI account number as the business identifier. In this respect, the methodology to identify establishments is equivalent to the Quarterly Census of Employment and Wages. See for more details Abowd and Vilhuber (2011).

[23] With the purpose of joining the information under a common industry classification, we use a correspondence table, provided by the National Bureau of Economic Research, which maps industry NAICS codes into industry SIC codes.

Figure 3.2. Aggregate employment in US manufacturing



Notes: Manufacturing employment based on the connected industry sample from *LRD* and *QWI*. *Aggregate* manufacturing employment based on tabulations from the Bureau of Labor Statistics.

macroeconomic uncertainty.[24] We document in Appendix 3.A.4 our results when using financial uncertainty.[25]

3.4.3 Frictions

We aim to understand whether uncertainty shocks affect the economy primarily through factor adjustment frictions, price rigidities, or financial frictions. For this purpose, we construct proxies of these frictions at the industry-level. The proxies are defined such that higher values imply higher degree of frictions at the industry.

3.4.3.1 Labor adjustment frictions

Labor market regulations are generally common to all industries within the same country. However, the underlying costs for raising hours worked, hiring or firing work-

[24] The authors provide proxies of uncertainty for three horizons: 1, 3, and 12 months. Our analysis is based on the uncertainty based on three months horizons, which coincides with the frequency used in our empirical analysis. Our findings are robust when using alternative horizons for the uncertainty proxy.

[25] Jurado et al. (2015) provides, additionally, the so-called firm-common uncertainty, which is based on the cross-sectional dispersion of firm profit growth from Compustat data. However, this time series extends only until 2011. For this reason, we focus on the alternative proxies.

ers may differ across industries. Following Botero et al. (2004), we use the share of full-time workers to proxy for the degree of flexibility of employment contracts and the cost to layoff workers at the industry. Further, we include the share of total workforce affiliated to labor unions to approximate for the power of the union at the industry.[26] Finally, we consider the kurtosis of the net employment growth distribution at the industry. As argued in Section 3.2.1, under the presence of non convex employment adjustment costs, labor adjustments are infrequent and lumpy, which creates excess kurtosis relative to a normal distribution.[27]

3.4.3.2 Capital adjustment frictions

The literature commonly infers the size of capital adjustment costs based on the distribution of cross sectional gross investment rate. For example, Cooper and Haltiwanger (2006) and Bachmann and Bayer (2014), document that micro-level gross investment rate exhibits substantial positive skewness and kurtosis. Non-convex capital adjustment costs are an important driver of this result. Given non-convexities, capital adjustments are infrequent and lumpy. As a usual adjustment is large, this leads to excess kurtosis. Moreover, as businesses may downward adjust capital through depreciation, negative gross investment is more unlikely and, therefore, we should expect positive skewness. Consequently, we consider the skewness and kurtosis of the gross investment rate distribution at the industry level to capture the size of capital adjustment costs.[28] In addition, we include the ratio of structures over equipment at the industry. In this respect, Caballero and Engel (1999) considers a dynamic capital adjustment costs model, and finds business-level costs to be more pronounced at structures relative to equipment.

[26] The share of full-time workers and union density are based on the March Supplements from the Current Population Survey, see Table 3.2. In order to map the industry classification from CPS into 1987 SIC we use a concordance table provided by David Dorn at http://www.dorn.net/data.htm.

[27] We compute the kurtosis of net employment growth at the industry if we have at least ten observations at the industry. Given that we lack of sufficient information at the 4-digit SIC level, we compute it at the 3-digit SIC level. Furthermore, for 10% of the industries, the information at the 3-digit SIC level is not available, so we impute it by the mean value at the 2-digit SIC level.

[28] We compute these moments if we have at least ten observations at the industry. Given that we lack of sufficient information at the 4-digit SIC level, we compute the indicators at the 3-digit SIC level. Furthermore, for 10% of the industries, the information at the 3-digit SIC level is not available, so we impute it by the mean value at the 2-digit SIC level.

3.4.3.3 Price rigidity

We construct price rigidity at the industry level based on estimates from Petrella and Santoro (2012). The authors consider sector specific New Keynesian Philips Curve (NKPC) to back-out the degree of price rigidity at the industry. They evaluate alternative proxies for marginal costs and different specifications of sectoral NKPC. We construct price rigidity at the industry as an average of the implied price adjustment probabilities based on the intermediate input share as a proxy for marginal costs, which fits best their model predictions.[29]

3.4.3.4 Financial frictions

Industries differ, due to the nature of the product, on the length of the production process, estimated time until cash from revenues realizes, among others. These differences affect plant's liquidity and borrowing needs, and consequently, its vulnerability to financial frictions.

Following Raddatz (2006), we construct measures of liquidity needs as the industry-level median ratio of inventories to sales, and labor costs to sales.[30] These variables capture the share of inventory investments or labor costs which can be commonly financed by revenues. As larger the values, higher is the need to rely on external sources to cover the expenditures. In principle, the constructed ratios may not be entirely technological. For example, businesses may opt to accumulate liquid assets to avoid financial dependence. To circumvent this problem, we follow the literature and construct the measures using information from publicly traded U.S. companies. The underlying assumption is that observed industry differences at these large publicly traded companies is not driven by the supply of credit, which is considered to be perfectly elastic.

[29] We do not consider the estimated price adjustment probabilities which are inconsistent with the theory. That is, we ignore those estimates where the implied probability is above one or below zero. For those industries with missing information of price rigidity, we impute their values based on the average price rigidity at the 3-digit SIC level.

[30] We consider only those industries with at least 5 firms at the industry. Given that we lack of sufficiently information at the 4-digit SIC level, we compute the indicators at the 3-digit SIC level. Furthermore, for 10% of the industries, the information at the 3-digit SIC level is not available, so we impute it by the mean value at the 2-digit SIC level.

We complement our index with the share of employment at young firms (below 5 years old) at the industry. There is ample evidence which associates larger borrowing costs at young businesses, as they have higher degree of idiosyncratic risk, lower amount of collateral, and weaker credit records.[31]

3.4.3.5 Summary

Table 3.2 describes the variables we use to measure industry-level frictions. To create these indexes, we consider the average from the standarized variables, and we further standarize the index itself.[32] We are able to construct the indicators for 443 manufacturing industries. Table 3.3 presents the correlations between the indexes. On the one hand, industries with larger capital adjustment costs are associated with larger labor adjustment costs. On the other hand, industries with higher vulnerability to financial conditions are commonly related with lower factor adjustment frictions.

[31] The literature used size of the business as alternative indicator for access to credit and tightness of the borrowing constraint. However, there is recent evidence which suggests that financial frictions do not lead to different business dynamics across firm size, once controlling by the age of the firm. See for example Hurst and Pugsley (2011), Dyrda (2015), and Fort et al. (2013).

[32] As alternative method, we construct the first principal component. Our main findings are robust to this specification, see Appendix 3.A.4.2.

Table 3.2. Variables reflecting frictions at the industry level

Variable	Description	Source
Labor frictions index		
Share of full time workers	Share of employees working full-time (35 hours or more) at the industry (average)	March CPS: 1970-2011
Unionization	Share of workers affiliated to labor unions at the industry (average)	March CPS: 1990-2011
Kurtosis employment growth	Kurtosis of the net employment growth distribution. Net employment growth defined as $\frac{L_{it+1}-L_{it}}{0.5*(L_{it}+L_{it+1})}$	Compustat: 1968-2006
Capital frictions index		
Structure intensity	Structures relative to equipment at the industry (average)	NBER-CES Manufacturing: 1958-2011
Skewness gross investment	Skewness of the gross investment rate distribution. Investment rates defined at the firm as $\frac{I_{it}}{0.5*(K_{it}+K_{it+1})}$	Compustat: 1968-2006
Kurtosis gross investment	Kurtosis of the gross investment rate distribution. Investment rates defined at the firm as $\frac{I_{it}}{0.5*(K_{it}+K_{it+1})}$	Compustat: 1968-2006
Price rigidity index		
Price adjustment probability	Based on the estimation of industry level New Keynesian Phillips curves	Petrella & Santoro (2012)
Financial frictions index		
Inventory cost share	Industry-level median of inventories over sales	Compustat: 1968-2006
Labor cost share	Industry-level median of labor costs over sales	Compustat: 1968-2006
Employment share at young firms	Average share of employment at young firms (below 5 years old)	Quarterly Workforce Indicators: 2000-2013

Table 3.3. Correlation between indexes

	Labor index	Capital index	Price index
Capital index	$.268^{***}$		
Price index	-.022	$-.03$	
Financial index	$-.311^{***}$	$-.083^{*}$	0.087^{*}

Notes: This table presents pairwise correlations between the indexes. See Table 3.2 for for a detail description of the industry indexes. Significance: 1% (***), 5% (**), 10% (*).

3.5 Results

3.5.1 Response to uncertainty shocks

We estimate industry-level impulse responses based on quarterly data from 1972Q2 to 2013Q4. As the information is at quarterly frequency, we use four lags in our VAR system. In order to account for the potential differences that may arise from joining the series from Davis et al. (1998) with QWI (see Section 3.4.1), we include a step dummy which takes the value of one from 2000Q2 onwards, and zero otherwise. Furthermore, we allow for different time trends at the first panel (1972-1998) and second panel (2000-2013).

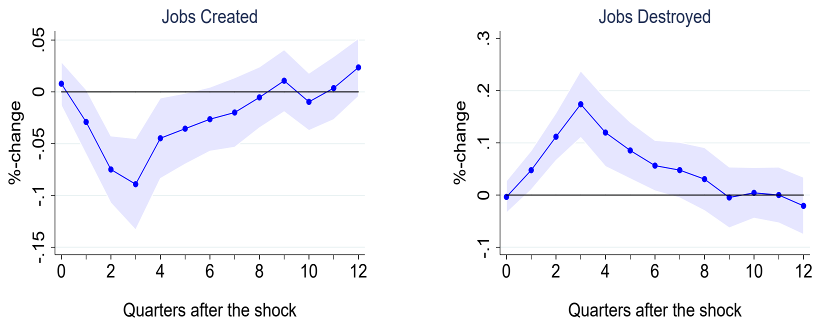
We start by characterizing the effects of an uncertainty shock on aggregate job flows. As described in Section 3.3, each model contains, as common variables, the stock-market level, uncertainty, and the aggregate job flows. Figure 3.3 displays the effects of an uncertainty shock on aggregate job flows based on this subsystem.

An uncertainty shock significantly decrease aggregate job creation and rise aggregate job destruction. These effects are not in line with the predictions based on a model with labor adjustment costs, see Section 3.2.1. In other words, we do not find supporting evidence of labor adjustment frictions as a transmission mechanism through which uncertainty affects job flows.

3.5.2 Through which channel uncertainty shocks affects employment?

To answer this question, we follow the econometric approach from Davis and Haltiwanger (2001), and regress the cumulative impulse responses from each industry on cubic polynomi-

Figure 3.3. Impulse response functions: Aggregate job flows

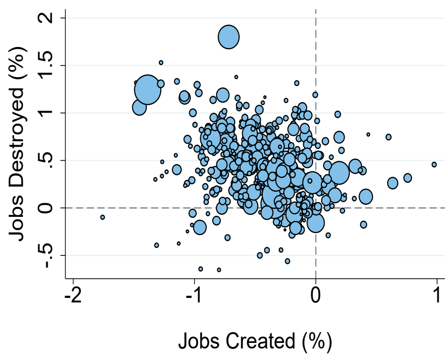


Notes: Impulse responses of aggregate job creation and job destruction given a three standard deviation uncertainty shock. Shaded area denotes 90% confidence interval, computed following a block bootstrap approach as Kilian and Kim (2009).

als in labor, capital, price, and financial index. We focus on the cumulative responses from the first year horizon, and report in Appendix 3.A.4.4 the results based on alternative horizons.

To begin with, Figure 3.4 summarizes the estimated cumulative responses of job flows to an uncertainty shock for all industries. For more than 80% of the industries, an unexpected rise of uncertainty leads to more jobs destroyed and less jobs created. As our previous finding, this result does not support labor adjustment costs as an important channel through which uncertainty affects job flows.

Figure 3.4. Cumulative response to an uncertainty shock: 4-digit industries



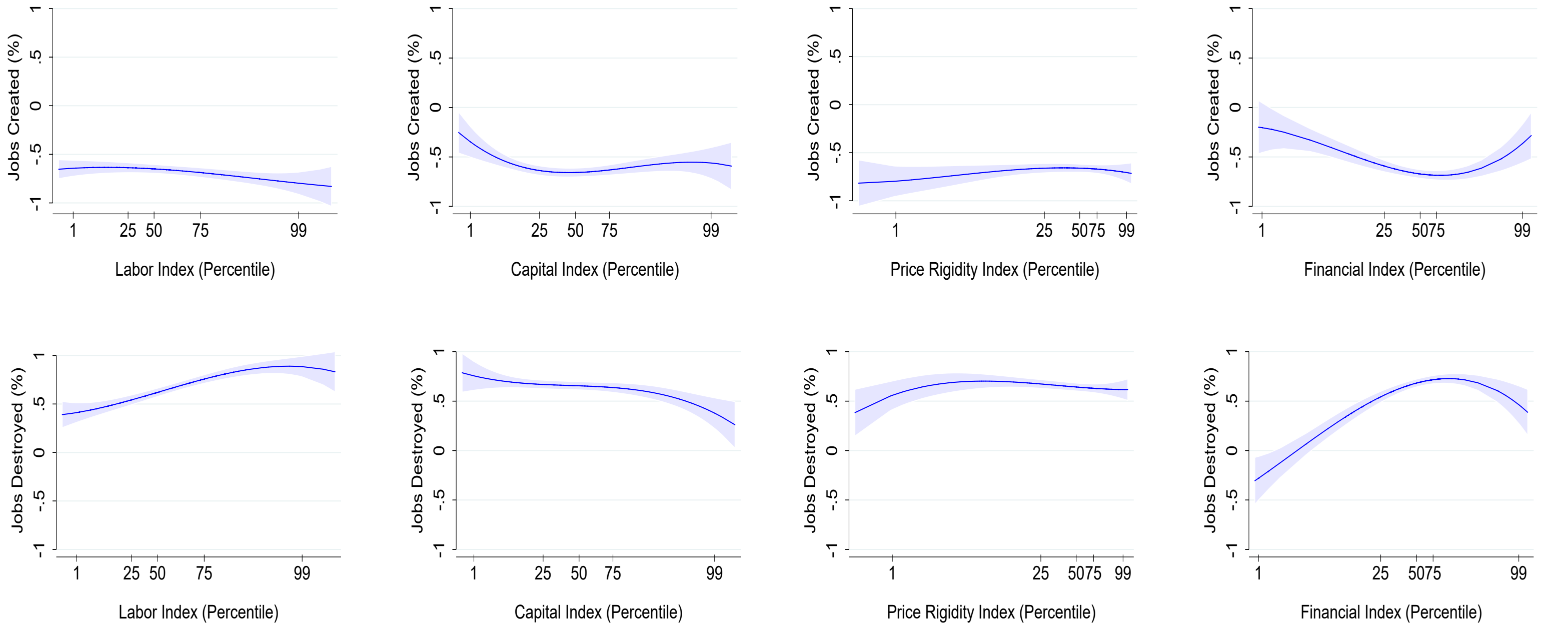
Notes: Cumulative response of job flows based on the first year horizon, given a three standard deviation uncertainty shock. The upper left quadrant contains 80% of the industries. Marker size represents the size of the industry relative to the aggregate employment in manufacturing in United States.

Figure 3.5 provides the fitted relationship between the cumulative job flow responses and each friction, while evaluating the remaining variables at the median.

Given our previous empirical findings, it remains to understand the role of capital, price, and financial frictions. We do not find supporting evidence of capital frictions and price rigidities as channels through which uncertainty affects job flows. While the share of jobs destroyed declines with the size of capital frictions at the industry, there is no significant relation between the decline in job creation and the size of capital adjustment frictions. Similarly, the relation between price rigidity and industry-level job flow responses is almost flat.

On the contrary, financial vulnerability seems to play an important role for explaining the effects of uncertainty shocks. As higher the vulnerability to financial conditions, stronger the response of job flows from an uncertainty shock. The effect is sizable. Industries associated to be most vulnerable to financial conditions (top quintile) report 75% stronger job flow responses than the least vulnerable industries (bottom quintile).

Figure 3.5. Cumulative response to a macro uncertainty shock conditional on industry indexes



Notes: Regressions are based on the industry-level cumulative response (first year horizon) given a three standard deviation macro uncertainty shock. We regress this variable as a function of a cubic polynomial of all industry indexes jointly. The predicted response is constructed allowing the indicated industry index to vary, while evaluating the remaining industry indexes at the median. Shaded areas denotes 90% confidence interval. We weight industry-level cumulative responses by the estimated absolute effect at the industry relative to the standard deviation of the estimate.

Table 3.4. Cumulative response to an uncertainty shock conditional on quintile indexes

	Job creation		Job destruction	
	Bottom Quintile	Top Quintile	Bottom Quintile	Top Quintile
Labor frictions index	-0.64	-0.75	0.49	0.85
	(0.04)	(0.04)	(0.05)	(0.04)
Capital frictions index	-0.55	-0.60	0.68	0.54
	(0.04)	(0.05)	(0.04)	(0.05)
Price rigidity index	-0.70	-0.70	0.66	0.62
	(0.05)	(0.04)	(0.05)	(0.04)
Financial frictions index	-0.45	-0.61	0.26	0.64
	(0.06)	(0.04)	(0.06)	(0.04)

Notes: Regressions are based on the industry-level cumulative response (first year horizon) given a three standard deviation uncertainty shock. We regress this variable as a function of a cubic polynomial of all industry indexes jointly. The predicted response is constructed allowing the indicated industry index to vary, while evaluating the remaining industry indexes at the median. Bottom (Top) quintile: Predicted job flows at the first (fifth) quintile of the industry index distribution. Standard errors in parenthesis.

3.5.3 Controlling for additional shocks

We assess whether our findings are robust if we consider a richer VAR system which allows us to further control for monetary and fiscal shocks. We augment our baseline specification with monetary and fiscal shocks identified through narrative approaches. For the former, we include the series of shocks identified by Coibion et al. (2012), while for the latter we consider the series from Mertens and Ravn (2014). Given data availability, the analysis is limited until 2006Q4.

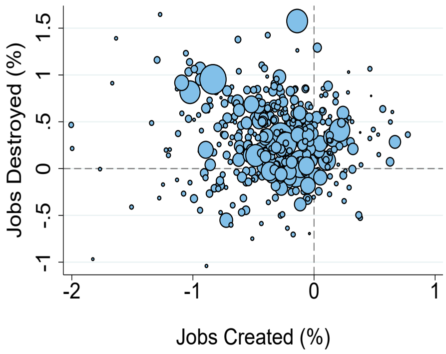
We place the tax and monetary shocks first in the recursive ordering. Further, we include additional restrictions at $A(L)$:

$$a_{i,jc}(l) = a_{i,jd} = 0, \; \forall l \; and \; i = m, x, s, u, ajc, ajd$$

where m denote the monetary policy shock and x the tax shock series, identified through narrative approaches.

Figures 3.6 and 3.7 provide the results from this exercise. For more than 60% of the industries, an uncertainty shock leads to more jobs destroyed and less jobs created. Further, the relation between the cumulative job flows responses and financial vulnerability is even stronger than our baseline results. Industries with the highest vulnerability to financial frictions are associated with 150% stronger job flow responses relative to the least vulnerable industries.

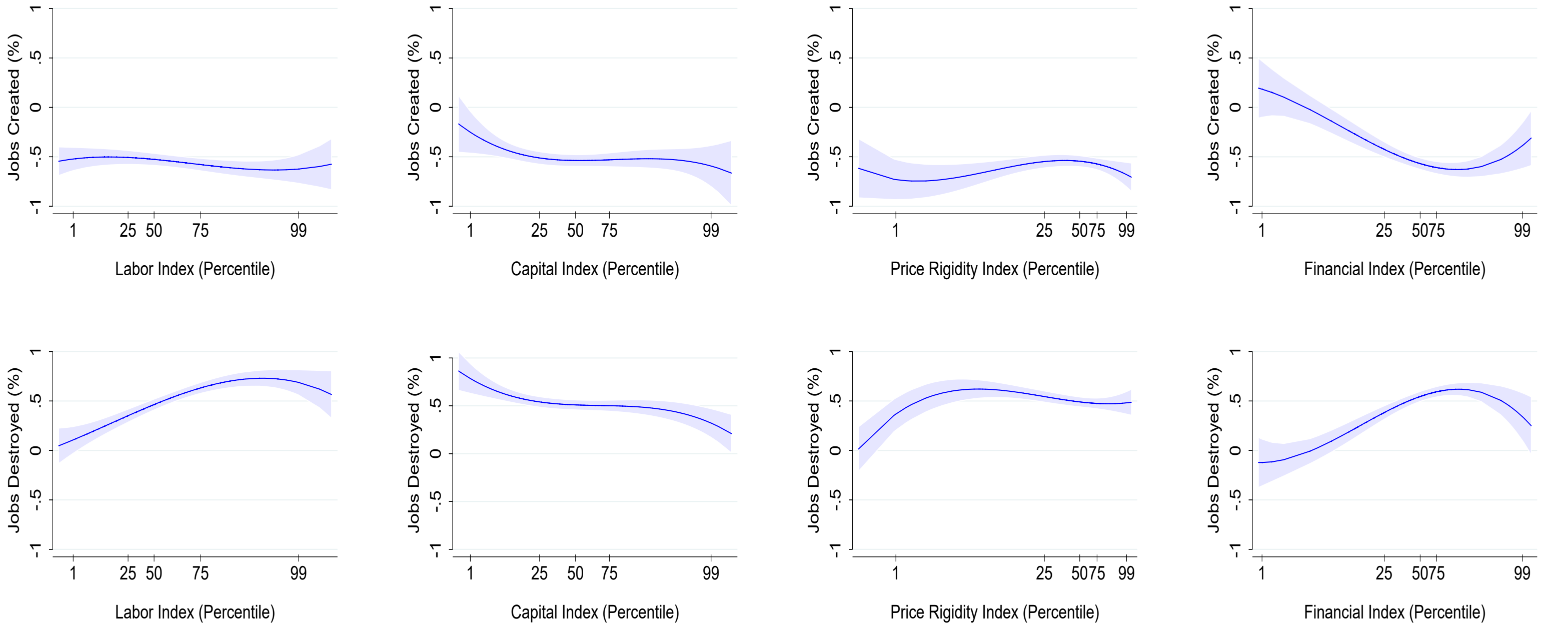
Figure 3.6. Cumulative response to an uncertainty shock: Controlling for monetary and fiscal shocks



Notes: Cumulative response of job flows based on the first year horizon, given a three standard deviation uncertainty shock. The upper left quadrant contains 60% of the industries. Marker size represents the size of the industry relative to the aggregate employment in manufacturing in United States.

In Appendix 3.A.4, we show that our empirical findings are robust whether we consider alternative horizons for the cumulative responses or use financial uncertainty as an alternative proxy of uncertainty. We also show that our findings hold if we focus exclusively on the series based on the first sample (1972-1998) or second sample (2000-2013).

Figure 3.7. Cumulative response to a macro uncertainty shock conditional on industry indexes: Controlling for monetary and fiscal shocks



Notes: Regressions are based on the industry-level cumulative response (first year horizon) given a three standard deviation uncertainty shock. We regress this variable as a function of a cubic polynomial of all industry indexes jointly. The predicted response is constructed allowing the indicated industry index to vary, while evaluating the remaining industry indexes at the median. Shaded areas denotes 90% confidence interval. We weight industry-level cumulative responses by the estimated absolute effect at the industry relative to the standard deviation of the estimate.

3.6 Conclusion

This paper assess whether factor adjustment frictions, price rigidities, or financial frictions are important transmission mechanisms through which uncertainty shocks affects the economy.

Using job flows data at the industry level over the period 1972-2013 in United States, we find that an uncertainty shock leads to more jobs destroyed and less jobs created for about 80% of the industries. The magnitude of these responses are particularly stronger as higher is the degree of vulnerability to financial conditions at the industry. On the contrary, we do not find supportive evidence of factor adjustment frictions or price rigidities as important channels of uncertainty shocks in the economy.

Our work highlights the importance of financial frictions as an important channel through which uncertainty affects the economy. One interesting avenue for further research would be to understand whether government policies can ameliorate the effects of uncertainty shocks in an economy with financial frictions, and whether these government interventions would be socially desirable.

Appendix 3.A Appendix

3.A.1 Computation

To solve the models, we discretize the state space. For the exogenous demand process z, we approximate it with 19 grid points with a Tauchen algorithm which takes into account time-varying volatility (see Bloom et al. (2014)). Furthermore, for the model with labor adjustment frictions, we choose 1000 log-linear grids points for labor. Similarly, in the model with capital adjustment frictions, we consider 1000 log-spaced grids with respect to depreciation. In the model with price rigidities, we further discretize the exogenous aggregate price process P with 15 grid points, applying again a Tauchen algorithm, and consider 900 log-spaced grid points for the price of the plant. Finally, for the financial frictions model, as the state space of the problem is relatively more complex with respect to the other dynamic problems, we consider a lower amount of grid points for the demand process. In particular, we approximate the demand process with 16 grid points, and consider 40 log-spaced grid points for labor, and 48 equidistant grid points for debt. We solve the models using value function iteration.

3.A.2 Model solution: Financial frictions

In order to numerically solve the model with financial frictions in Section 3.2.4 we consider the following steps:

1. Guess the price for the bond the value of the plant.
2. Given the bond price, calculate the value function using value function iteration.
3. Using the updated value function, construct the default function and update the bond price.
4. Based on the updated bond price, return to point 1 until the price of the bond convergences.

3.A.3 Data description

We use a concordance table provided by the National Bureau of Economic Research (NBER) to connect the disaggregated information at the 4-digit 1987 SIC level from Davis et al. (1998) with the data series from QWI which is disaggregated at 4-digit 2007 NAICS level.[33] This table allows us to map industry codes using weights, which links the share of employment at the SIC level which corresponds to an industry in NAICS. Yet, before proceeding with this concordance, we need to conduct some adjustments.

First, the available concordance between SIC and NAICS is based on the 1997 NAICS. Therefore, we translate 6-digit 2007 NAICS into 6-digit 1997 NAICS using the table given by US Census Bureau at http://www.census.gov/eos/www/naics/concordances/concordances.html. Second, we adjust the concordance table from the 6-digit NAICS level to the 4-digit NAICS level, and re-compute the weights from SIC into NAICS based on the share of employment of the 6-digit NAICS industry at the 4-digit NAICS level. At the end, we are able to map all industry-level job flows from NAICS with the data from Davis et al. (1998).

3.A.4 Robustness

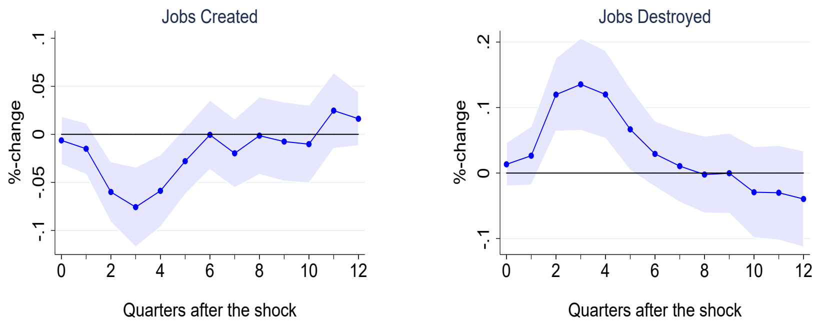
3.A.4.1 Job flow responses from a financial uncertainty shock

Figures 3.8 and Table 3.5 show the effect of uncertainty shocks on job flows when using financial uncertainty as a proxy for uncertainty. Ludvigson et al. (2015) make a distinction

[33] The table can be access at http://www.nber.org/nberprod/.

between macroeconomic and financial uncertainty where the latter seems to have larger negative impact on real economic activity. Yet, the quantitative effect on job flows and its relation with the industry indexes are remarkably similar to our baseline results, when using as a proxy macroeconomic uncertainty.

Figure 3.8. Impulse response functions given a financial uncertainty shock: Aggregate job flows



Notes: Impulse responses of aggregate job creation and job destruction given a three standard deviation uncertainty shock. Shaded area denotes 90% confidence interval, which is computed following a block bootstrap approach as Kilian and Kim (2009).

3.A.4.2 Results based on the first principal component

In the following, we show that our main results are robust if we consider an alternative method to construct the indexes at the industry-level. In particular, we construct the indexes as the first principal component of the variables which corresponds to each index.

Table 3.5. Cumulative response to a financial uncertainty shock conditional on quintile indexes

	Job creation		Job destruction	
	Bottom Quintile	Top Quintile	Bottom Quintile	Top Quintile
Labor frictions index	-0.63	-0.65	0.50	0.73
	(0.04)	(0.05)	(0.05)	(0.04)
Capital frictions index	-0.59	-0.58	0.64	0.52
	(0.04)	(0.05)	(0.04)	(0.05)
Price rigidity index	-0.61	-0.63	0.60	0.57
	(0.05)	(0.04)	(0.06)	(0.04)
Financial frictions index	-0.52	-0.64	0.22	0.57
	(0.05)	(0.04)	(0.06)	(0.04)

Notes: Regressions are based on the industry-level cumulative response (first year horizon) given a three standard deviation uncertainty shock. We regress this variable as a function of a cubic polynomial of all industry indexes jointly. The predicted response is constructed allowing the indicated industry index to vary, while evaluating the remaining industry indexes at the median. Bottom (Top) quintile: Predicted job flows at the first (fifth) quintile of the industry index distribution. Standard errors in parenthesis.

3.A.4.3 Effects from uncertainty shocks in the first and second sample of analysis

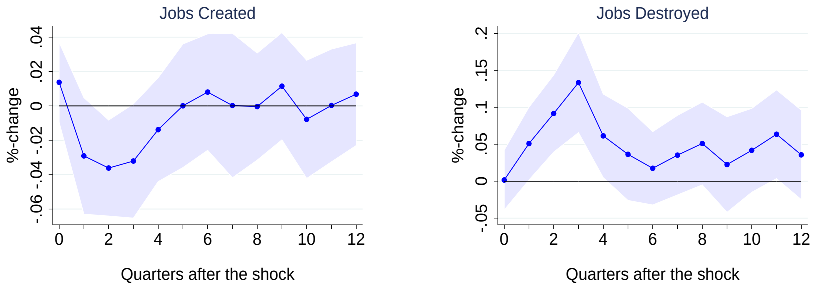
We explore whether our findings hold if we focus on the first sample of analysis (1972-1998), see Figures 3.9 and Table 3.7, and second sample of analysis (2000-2013), see Figures 3.10 and 3.7. While the samples differ in regards to the quantitative effect of uncertainty shocks, as higher the vulnerability to financial frictions, stronger is the effect of uncertainty shocks on job flows at both series.

Table 3.6. Cumulative response to an uncertainty shock conditional on quintile indexes (principal component)

	Job creation		Job destruction	
	Bottom Quintile	Top Quintile	Bottom Quintile	Top Quintile
Labor frictions index	-0.70	-0.77	0.52	0.86
	(0.04)	(0.04)	(0.05)	(0.04)
Capital frictions index	-0.52	-0.60	0.65	0.58
	(0.04)	(0.05)	(0.04)	(0.05)
Price rigidity index	-0.71	-0.72	0.66	0.62
	(0.05)	(0.04)	(0.05)	(0.04)
Financial frictions index	-0.48	-0.62	0.25	0.66
	(0.06)	(0.04)	(0.06)	(0.04)

Notes: Regressions are based on the industry-level cumulative response (first year horizon) given a three standard deviation uncertainty shock. We regress this variable as a function of a cubic polynomial of all industry indexes jointly. Industry indexes are constructed as a function of the first principal component of the variables at the industry-level. The predicted response is constructed allowing the indicated industry index to vary, while evaluating the remaining industry indexes at the median. Bottom (Top) quintile: Predicted job flows at the first (fifth) quintile of the industry index distribution. Standard errors in parenthesis.

Figure 3.9. Impulse response functions: Aggregate job flows (Sample 1972-1998)



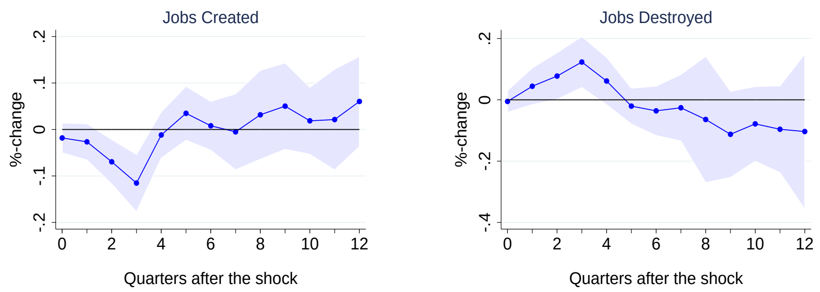
Notes: Impulse responses of aggregate job creation and job destruction given a three standard deviation uncertainty shock. Shaded area denotes 90% confidence interval, which is computed following a block bootstrap approach as Kilian and Kim (2009).

Table 3.7. Cumulative response to an uncertainty shock conditional on quintile indexes: Sample 1972-1998

	Job creation		Job destruction	
	Bottom Quintile	Top Quintile	Bottom Quintile	Top Quintile
Labor frictions index	-0.58	-0.70	0.33	0.86
	(0.06)	(0.07)	(0.07)	(0.06)
Capital frictions index	-0.55	-0.67	0.68	0.51
	(0.07)	(0.07)	(0.06)	(0.07)
Price rigidity index	-0.71	-0.70	0.57	0.51
	(0.08)	(0.06)	(0.07)	(0.06)
Financial frictions index	-0.31	-0.56	0.12	0.57
	(0.09)	(0.07)	(0.08)	(0.06)

Notes: Regressions are based on the industry-level cumulative response (first year horizon) given a three standard deviation uncertainty shock. We regress this variable as a function of a cubic polynomial of all industry indexes jointly. The predicted response is constructed allowing the indicated industry index to vary, while evaluating the remaining industry indexes at the median. Bottom (Top) quintile: Predicted job flows at the first (fifth) quintile of the industry index distribution. Standard errors in parenthesis.

Figure 3.10. Impulse response functions: Aggregate job flows (Sample 2000-2013)



Notes: Impulse responses of aggregate job creation and job destruction given a three standard deviation uncertainty shock. Shaded area denotes 90% confidence interval, which is computed following a block bootstrap approach as Kilian and Kim (2009).

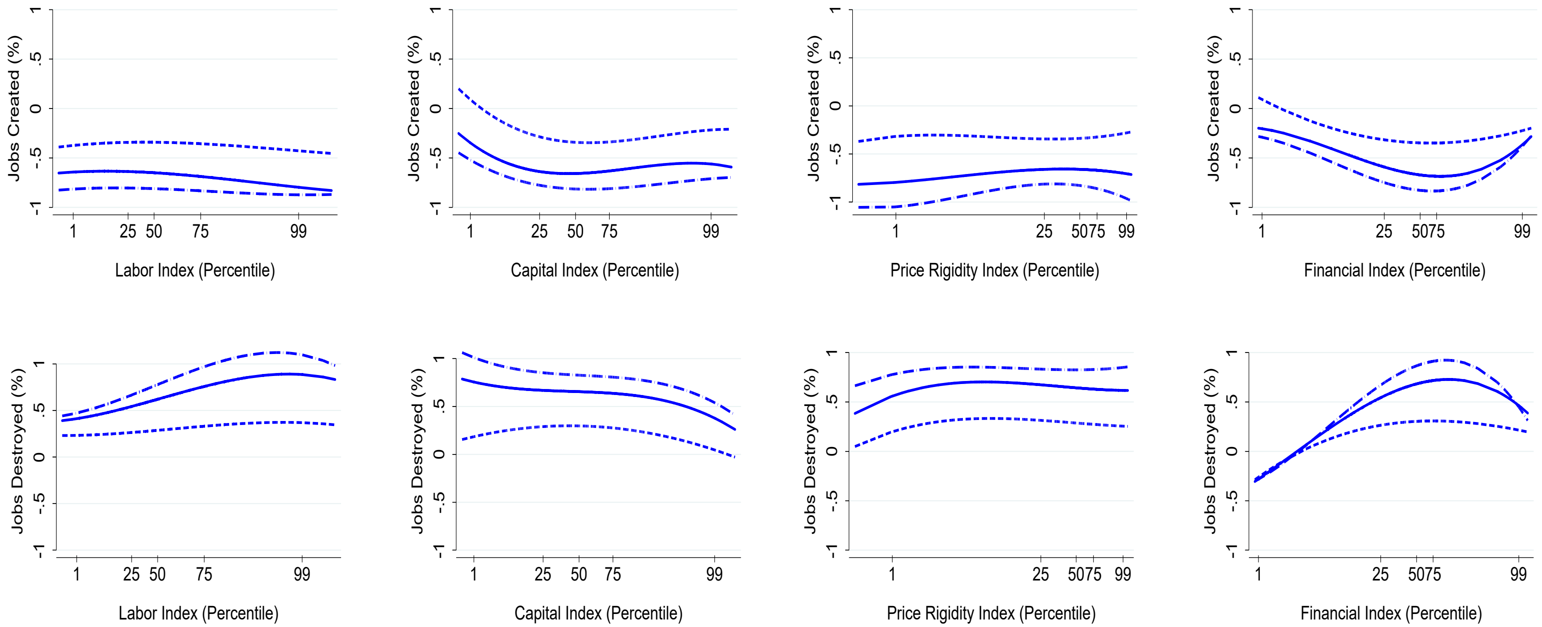
Table 3.8. Cumulative response to an uncertainty shock conditional on quintile indexes: Sample 2000-2013

	Job creation		Job destruction	
	Bottom Quintile	Top Quintile	Bottom Quintile	Top Quintile
Labor frictions index	-0.31	-0.42	0.40	0.50
	(0.02)	(0.03)	(0.02)	(0.02)
Capital frictions index	-0.42	-0.33	0.47	0.37
	(0.03)	(0.03)	(0.02)	(0.02)
Price rigidity index	-0.36	-0.29	0.42	0.40
	(0.03)	(0.02)	(0.02)	(0.02)
Financial frictions index	-0.28	-0.31	0.20	0.41
	(0.03)	(0.03)	(0.04)	(0.02)

Notes: Regressions are based on the industry-level cumulative response (first year horizon) given a three standard deviation uncertainty shock. We regress this variable as a function of a cubic polynomial of all industry indexes jointly. The predicted response is constructed allowing the indicated industry index to vary, while evaluating the remaining industry indexes at the median. Bottom (Top) quintile: Predicted job flows at the first (fifth) quintile of the industry index distribution. Standard errors in parenthesis.

3.A.4.4 Alternative horizons: Cumulative job flow responses

Figure 3.11. Cumulative response to a macro uncertainty shock conditional on industry idexes: Alternative horizons of cumulative responses



Notes: Regressions are based on the industry-level cumulative response of two (dashed line), four (solid line), and six quarter (dashed-dot line) horizon, given a three standard deviation macro uncertainty shock. We regress this variable as a function of a cubic polynomial of all industry indexes jointly. The predicted response is constructed allowing the indicated industry index to vary, while evaluating the remaining industry indexes at the median. Shaded areas denotes 90% confidence interval. We weight industry-level cumulative responses by the estimated absolute effect at the industry relative to the standard deviation of the estimate.).

4

Wage Risk, Employment Risk and the Rise in Wage Inequality

Joint with Felix Wellschmied

4.1 Introduction

Individuals face substantial idiosyncratic earnings uncertainty in the labor market.[1] Whether this risk has changed over the last decades is a key question to comprehend changes in earnings inequality, the welfare costs of incomplete markets, and to appropriately redesign the welfare state. Yet, no consensus has been reached.[2]

In this study, we quantify trends in labor market risks over the last three decades in the US. We estimate risk resulting from idiosyncratic shocks to a worker's productivity that change his market wage irrespective of his current job. Moreover, we identify the risk arising from different jobs paying heterogeneous wages for the same worker. In the presence of search frictions, a worker is not able to locate the highest paying job instantaneously, implying a risk component arising from job search. The distinction between productivity and a job component is pertinent from the worker perspective. A worker may choose exiting the labor market when his idiosyncratic skills are suddenly less demanded. On the contrary, when facing a specific job offer, a worker has the option to accept it or to stay with his current job.

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[1] For early contributions see Lillard and Willis (1978), Lillard and Weiss (1979) and MaCurdy (1982).

[2] Early studies like Gottschalk and Moffitt (1994), Blundell et al. (2008), and Heathcote et al. (2010b) find income uncertainty to have increased. Recent evidence by CBO (2007) and Guvenen et al. (2014) do not find such secular trends.

Different from the existing empirical literature on trends in labor market risk, we disentangle these endogenous choices from the shocks that triggered them. As Low et al. (2010) and Altonji et al. (2013), we uncover the true variances of shocks from observed wage changes by explicitly modeling participation and job-mobility decisions as reaction to these shocks. The amount of endogenous selection of workers upon shocks depends on the distribution of worker types and the institutional setting. Both of these changed considerably since the 1980's in the US; the share of workers with weak labor market attachment has grown, and the welfare state became more generous in many instances (see Ben-Shalom et al. (2011)). To account for these changes, we allow the amount of selection in the data to have secular trends of its own.

Using panel data from the Survey of Income and Program Participation (SIPP) for males over the period 1983-2013, we find that differentiating between different types of risk and accounting for selection is important. While observed quarterly wage volatility is close to constant over time, the standard deviation of permanent risk has increased between 16 and 30 percent, depending on workers' education.[3] Moreover, heterogeneity in job offers increased over time for workers with at least some college education. On the contrary, this dispersion decreased for workers with at most high school education, particularly, when changing careers.

To quantify the role that these changes in risk play in explaining rising wage inequality and their consequences for social welfare, we simulate the estimated risk in a structural partial equilibrium model of life-time utility maximization. Workers' productivity evolves stochastically, and workers search for jobs, on and off the job, paying heterogeneous wages for a given productivity level. Utility for leisure and precautionary savings provide partial insurance against uncertainty arising from job offers and productivity. Additionally, our model puts emphasis on the insurance provided by the government and the resulting employment decisions. Workers have access to unemployment insurance, a means-tested program, disability insurance, and social security. Furthermore, the government runs a progressive tax schedule. We find the model provides a good fit of key data moments given the estimated wage process. Moreover, it features selection into employment and across jobs consistent with our data estimates. When simulating the increase in estimated risk, the model can account

[3] We find a declining trend in transitory wage innovations, yet, this may reflect changes in measurement error.

for 85% of the increase in within group wage inequality in United States during the last three decades.[4]

Other papers which use structural models of the labor market to understand trends in wage inequality are Bowlus and Robin (2004), who permit for trends in wage promotions and demotion rates, Flabbi and Leonardi (2010), who consider trends in labor market transitions and job heterogeneity, and Leonardi (2015), who models changes to the dispersion of match specific productivity shocks. Our model differs from this literature by explicitly modeling a rich set of governmental programs, workers selecting into these, and by allowing jointly for productivity and wage offer risk.

We find that those dimensions are important to comprehend the welfare effects of changing labor market risk. The overall welfare costs of rising wage uncertainty are small. An unborn worker is willing to pay 0.23% of life-time consumption to avoid the increase in risk. This is in contrast to the large welfare costs of changed income risk found in Heathcote et al. (2010a). We differ in three main aspects. First, our estimated increase of permanent productivity risk is significantly smaller than theirs. Second, workers with higher educational degree compensate an increase of permanent risk with more dispersed job offers. These workers are willing to pay between 0.25% and 0.32% of life time consumption for an 0.01 increase in the standard deviation of job offers. The intuition is simple. In a search model, a rise in the dispersion of job offers creates an option value to the worker: Particular poor jobs terminate early because search allows the worker to find a better job. Third, we find the government plays a crucial role in insuring workers. Welfare losses from changing wage risk would be about five times larger when the government provides only social security.

Using small increases in the welfare state as counterfactual experiments, we ask whether the welfare state present in the 1980s was efficient in insuring workers against labor market risk. Consistent with Chetty (2006), we find that the complementarity of employment and consumption is quantitatively low, therefore, our model favors programs with low employment disencentive effects. Consequently, an increase in unemployment benefits reduces welfare, but an increase in universal means-tested transfers leads to a moderate welfare gain. The latter program provides insurance against persistent wage losses, but has only moderate employment disincentives. Autor and Duggan (2006) show that eligibility requirements for disability insurance were weakened over the last decades, and this threatens its financial

[4] We concentrate on the rise of within group wage inequality, which explains most of the rise in total residual inequality (see Krueger and Perri (2006)). We see our paper as complement to the literature focusing on between group inequality. This includes a rising college premium (Katz and Autor (1999)) and skill biased technological change (Katz and Murphy (1992)).

soundness. We find that such a weakening implies substantial welfare losses. The losses occur because disability insurance provides incentives for elderly workers with poor past outcomes to quit the workforce.

The structure of the paper continues as follows: The next section specifies our econometric model, discusses identification, and presents the results of changing wage uncertainty over time. The following section presents our life-cycle model, discuses the implications of changing wage uncertainty for wage inequality and discuses its welfare implications. The last section concludes.

4.2 Estimating Changes in Risk

4.2.1 Identification of Risk and Selection

Workers differ in their amount of log human capital u_{it}, which follows a random walk with exogenous innovations $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$. These shocks contain promotion decisions, health shocks, and any other changes in the market value of a worker's skills. In addition to human capital, wages depend on a log job component ψ_{ij}, which stays constant for the duration of the job. Our framework allows us to be silent about the source of this job component. It may arise from different firms paying different wages, or from an individual match component between the worker and the firm. Within a quarter, workers may receive up to one outside job offer from a wage offer distribution. Outside offer draws are random across time with $\psi_{ij} \sim N(0, \sigma_\psi^2)$. Consequently, the real log wage of individual i working at job j at time t is given by

$$\begin{aligned} w_{ijt} &= \beta x_{it} + \psi_{ij} + u_{it} + e_{it} \\ u_{it} &= u_{it-1} + \epsilon_{it} \\ e_{it} &= \mathscr{X}(q)\iota_{it}, \end{aligned} \tag{4.1}$$

where x_{it} is a vector of worker observables, and e_{it} is a transitory component, which follows an $MA(q)$ process with $\iota_{it} \sim N(0, \sigma_\iota^2)$. The latter may be true temporary wage shocks, such as bonuses, or measurement error in the data. Given his newly realized human capital, current job component, and possible outside offer, an individual decides each quarter whether to work and, conditional on working, whether to move to another job. The focus of this paper is on the dispersion of ϵ and ψ. For tractability, we assume that workers do not select on purely transitory shocks which may lead to a wrong inference of their size.[5]

The above representation embraces a large class of search models, yet, it is instructive to discuss the key assumptions. First, we assume a time invariant job component which is in line with on-the-job search models following Burdett and Mortensen (1998) and empirical specifications following Abowd et al. (1999). Relatedly, Guiso et al. (2005) show that firms almost perfectly insure workers against idiosyncratic firm risk, supporting our assumption. However, in the presence of some commitment device on the firm side, wages may be back loaded within a job with stable productivity (see Postel-Vinay and Robin (2002), and Burdett and Coles (2003)). Yet, Low et al. (2010) find that a model of stochastic job component fits the data worse than a model with a stochastic human capital component.[6] Second, we assume human capital to follow a random walk process, in line with a large empirical literature on earnings uncertainty.[7] Recently, Guvenen et al. (2015) show that estimating an $AR(1)$ mixture model of highly persistent and more transitory shocks helps to match the kurtosis and skewness present in earnings growth data. Extending our model including this process is beyond the scope of this paper. Given our decomposition of wages, we require that the excess kurtosis is not estimated as large variance of the permanent shock. We trim the distribution of wage growth and find that only the variance from transitory shocks is significantly affected.[8]

Taking first differences of Equation 4.1 yields individual wage growth:

$$\Delta w_{ijt} \;=\; \beta \Delta x_{it} + \underbrace{[\psi_{ij} - \psi_{ij-1}]}_{\xi_{it}} M_{it} + \epsilon_{it} + \Delta e_{it}, \tag{4.2}$$

where M_{it} is an indicator variable equal to one when the worker changes his job between t and $t-1$. Central to our approach, observed wage growth realizations result from endogenous labor market participation and job mobility decisions. Naturally, these decisions depend on the worker's current wage prospects, as well as the shock to his human capital and outside offers. We model these decisions using latent variables for participation in the current and

[5] We assume a $MA(2)$ process for transitory shocks e_{it}. Consequently, we identify this component from the autocovariance function of wage growth up to lag three. The estimated results are robust to alternative order specifications for the MA process.

[6] Along this line, Flinn and Mabli (2008), Hagedorn and Manovskii (2010), and Tjaden and Wellschmied (2014) show some counter-factual implications of wage back loading.

[7] See, for example, Abowd and Card (1989), Topel (1991), Topel and Ward (1992), Meghir and Pistaferri (2004) and Low et al. (2010).

[8] Heathcote et al. (2010b) find the same phenomenon in PSID data.

previous period, and job mobility:

$$P^*_{it-1} = \alpha z_{it-1} + \pi_{it-1}, \; P_{it-1} = 1\left\{P^*_{it-1} > 0\right\}, \tag{4.3}$$

$$P^*_{it} = \alpha z_{it} + \pi_{it}, \; P_{it} = 1\left\{P^*_{it} > 0\right\}, \tag{4.4}$$

$$M^*_{it} = \theta \kappa_{it} + \mu_{it}, \; M_{it} = 1\left\{M^*_{it} > 0\right\}, \tag{4.5}$$

where z_{it} and κ_{it} are worker observables, and π_{it} and μ_{it} are unobservables. The unobservable components contain, among other things, the unobserved human capital, its innovations ϵ_{it}, and the job component ψ_{ij}. To account for the arising correlation between the unobservables, we extend the framework of Low et al. (2010) and assume:

$$\begin{pmatrix} \pi_{it-1} \\ \pi_{it} \\ \mu_{it} \end{pmatrix} \sim \mathcal{N}\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{\pi\pi_{-1}} & \rho_{\pi\mu} \\ \rho_{\pi\pi-1} & 1 & \rho_{\pi_{-1}\mu} \\ \rho_{\pi\mu} & \rho_{\pi_{-1}\mu} & 1 \end{pmatrix}\right].$$

We estimate Equations 4.3-4.5 together with the covariance matrix using a nested trivariate probit, taking into account that mobility is only observed conditional on the individual having worked the current and previous quarter.[9]

Similar to a standard Heckit model, we use exclusion restrictions, discussed below, to obtain unbiased estimates of unexplained wage growth:[10]

$$g_{it} = \Delta w_{it} - \beta \Delta x_{it} = \xi_{it} M_{it} + \epsilon_{it} + \Delta \mathscr{X}(q) \iota_{it}. \tag{4.6}$$

Resulting from the participation and mobility decisions, the distribution of observed residual wage growth is truncated; we do not observe all shocks to productivity and the job component. Given the structure of our problem, residual wage growth follows a truncated multivariate normal distribution, which first two moments are derived in generic form by Manjunath and Wilhelm (2012).[11] To provide some intuition for identification, denote the correlation between permanent wage shocks and the unobserved component of participation by $\rho_{\epsilon\pi}$, and the correlation between the former and the unobserved component of mobility by $\rho_{\epsilon\mu}$. Further, define $\rho_{\xi\pi}$, $\rho_{\xi\pi-1}$ and $\rho_{\xi\mu}$ to be the correlation between changes in the job component and shocks to participation this period, last period, and mobility, respectively. Summarize

[9] We compute the multivariate normal probabilities using simulated maximum likelihood methods as in Cappellari and Jenkins (2006).

[10] Appendix 4.A.1 derives the appropriate selection term.

[11] Appendix 4.A.1 derives the moments for our particular case.

the results from the probit by the vector $X_{it} = [\alpha z_{it}, \alpha z_{it-1}, \theta\kappa_{it}, \rho_{\pi\pi_{-1}}, \rho_{\mu\pi}, \rho_{\mu\pi_{-1}}]$, then the first moments of unexplained wage growth in implicit form are given by

$$E(g_{it}|P_{it} = P_{it-1} = 1, M_{it} = 0) = \rho_{\epsilon\pi}\sigma_{\epsilon}\phi(-z_{it}\alpha)f_1(X_{it}) - \rho_{\epsilon\mu}\sigma_{\epsilon}\phi(\theta\kappa_{it})f_2(X_{it})$$
$$E(g_{it}|P_{it} = P_{it-1} = 1, M_{it} = 1) = \sigma_{\epsilon}\Big[\rho_{\epsilon\pi}\phi(-z_{it}\alpha)f_3(X_{it}) + \rho_{\epsilon\mu}\phi(-\kappa_{it}\theta)f_4(X_{it})\Big]$$
$$+ \sigma_{\xi}\Big[\rho_{\pi\xi}\phi(-z_{it}\alpha)f_5(X_{it}) + \rho_{\mu\xi}\phi(-\kappa_{it}\theta)f_6(X_{it}) + \rho_{\pi_{it-1}\xi}\phi(-z_{it-1}\alpha)f_7(X_{it})\Big],$$

where ϕ is the PDF of the standard normal distribution and f_x are functions that we show in closed form in Appendix 4.A.1. The first moments identify the correlations between wage innovations with mobility and participation decisions, up to the scalars σ_{ϵ} and σ_{ξ}. Identification results from comparing unexplained wage growth of individuals with different participation and mobility probabilities. Abstracting for the moment from measurement error, the second moments of unexplained wage growth achieve joint identification of σ_{ϵ}, σ_{ξ}, and selection correlations. Accounting for selection, the variance of wage growth of job stayers, $E(g_{it}^2|P_{it} = P_{it-1} = 1, M_{it} = 0)$, is sufficient to identify σ_{ϵ}. Moreover, the variance of wage growth of job switchers, corrected for selection, identifies σ_{ξ}. Finally, the combination of these four moments, together with the autocovariance function of wage growth, allows us to identify all parameters of interest.

4.2.2 Data Sources and Sample Selection

Our analysis of labor market risk requires individual longitudinal information on wages and worker and job characteristics over several decades. The dataset most adequate for these requirements is the Survey of Income and Program Participation (SIPP). It provides a set of panels covering the period of 1983-2013.[12] Every 4 month (defined as a wave) the Census conducts an interview with all adult members of participating households, asking them about their work and household characteristics during the preceding 4 months. In order to account for the seam-bias effect generated by the recollection period, we aggregate the monthly information to quarterly observations. One concern regarding the data is that the quality from the survey changed over time. We describe the details of our data cleaning procedure in Appendix 4.A.2, where we also show that survey redesigns are unlikely to have an impact on our main results.

[12] We exploit all up to date surveys, except of the survey from 1985 and 1989: 1984, 1986, 1987, 1988, 1990, 1991, 1992, 1996, 2001, 2004, and 2008. We do not these two surveys due to the absence of information regarding work experience, which is used at our estimation strategy.

We group the data into three major time periods, such that each covers years of expansion and recession: 1983-1993, 1994-2003, and 2004-2013. For the analysis, we consider three education groups based on the maximum attainable degree level: high school, college dropouts, and college graduates or higher education.[13] Furthermore, we focus on working-age male individuals, aged between 25 and 61, who are not self-employed, enrolled in school, in the armed forces, or recalled by their previous firm after a separation.[14]

Given the aggregation of the information at quarterly frequency, we need to establish some definitions with respect to employment and job-mobility at this frequency level. We consider a worker employed within a quarter, when he spends most weeks of the quarter working. We identify different jobs by the establishment ID assigned by SIPP.[15] We define a worker's main job based on the establishment ID with the highest earnings.[16] Whenever the main job changes from one quarter to the other, we count this worker as a job mover. Thus, mobility may result from job changes that occur either via a non-employment or without a non-employment spell.[17] For each quarter, we compute hourly wages as total earnings over total hours worked at the main job. To make the results robust to outliers, we do not consider individuals with hourly wage growth below the 1st percentile (above the 99th percentile) of the hourly wage growth distribution by education, period, and job mobility status.

4.2.3 Empirical Results

4.2.3.1 Probit Results

We estimate the model for each of our three periods and education degrees separately; thereby, we allow for time varying returns to human capital and time varying patterns in participation and mobility. In order to estimate the participation probability, we control for a quadratic in age and work experience, race, marital status, indicators whether a person

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[13] In specific, we group individuals into workers with at most high school education (high school), workers with some college and excluding individuals who received an associate degree (college dropouts), and workers who received an associate degree, college or higher (college degree).

[14] We choose the sample to start at age 25 to assure that college graduates fully transit to the labor market. Workers being recalled posses a search technology not well represented by our model.

[15] Our choice implies that we interpret within establishment changes in occupation as productivity shock and not as a change in the job component.

[16] The survey reports at most two jobs per month for each individual. In case an individual holds more than two jobs, the two jobs with most hours worked are reported.

[17] For identification, we require that skill depreciation for unemployment less than one quarter is negligible. Based on our employment definition, a worker with a mobility can have spend at most 2 months in unemployment.

lives in a metropolitan area or reports being disable, the unemployment rate at the state level, and time and region fixed effects.[18] Importantly, we require a set of regressors that identify selection. That is, variables affecting the decision to particpate or move jobs, but not independently related to ϵ_{it} and ξ_{it}. For this purpose, we augment the set of explanatory variables including unearned household income, an index of generosity of the welfare system (state-level unemployment insurance), and an indicator whether the worker owns a house.[19]

Additionally, we include industry and occupation fixed effects to estimate the probability to move jobs.[20] We present the results of the probits in Appendix 4.A.4. As expected, high unemployment benefits, high unearned income, and not owning a house reduce the probability to be employed. The theoretical effects on mobility are ambiguous. In principle, being closer to the participation margin should increase mobility because workers are more likely to quit their current job. On the other hand, higher reservation wages limit the possibility of future mobility. We find that state level generosity and house ownership reduce the likelihood of a worker to move jobs. In this respect, we do not find significant effects of unearned household income.

The amount of workers close to the participation and mobility margin is key for the severeness of workers selecting on shocks. We observe substantial changes along this margins over the decades under analysis. In particular, when comparing the third period with respect to the first, employed workers have relatively lower participation probabilities, with more workers in the lower tail of the distribution. Moreover, workers have higher probabilities to change jobs. When decomposing effects, we find that observable worker characteristics have shifted in the direction of workers with less stable jobs (singles, minorities, elderly), and the marginal effects of these covariates have also changed.

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[18] The survey provides, in addition, information regarding tenure at the job. Yet, the share of observations with reported zero values conditional on working is above 30%. Moreover, tenure information is not available for all jobs before the 1996 panel. Consequently, we opt not to use this variable for our analysis.

[19] As our study, Low et al. (2010) considers unearned household income and state-level unemployment insurance as exclusion restrictions in their estimation. For these exclusion restrictions to be valid we require that unemployment insurance payments do not affect wage growth through bargaining. In respect of the housing exclusion restriction, the literature considers it a predictors of job mobility while not affecting directly wage growth (see for example Blanchflower and Oswald (2013), Bowen and Finegan (2015)).

[20] For the estimation of the wage growth equation we control for industry dummies and their changes, and changes in occupations as they may be related to changes in the job component. Low et al. (2010) assume that there are no industry shocks driving mobility, while we assume that there are no within industry occupation specific shocks driving it.

4.2.3.2 Wage Variance Estimates and Selection

This section presents the estimated correlations and risk components. Estimation is based on minimizing the sum of squared residuals from the first and second moments of Equation 4.6 and the autocovariance terms, where we weight each individual contribution with the underlying survey weight.[21] We compute standard errors by the block-bootstrap procedure proposed by Horowitz (2003).

Figure 4.2 displays the point estimates for wage risk. Appendix 4.A.6 contains the corresponding estimated standard errors and the estimated correlations. All workers face substantial permanent shocks to their human capital, and those shocks become more dispersed with education. Furthermore, we find large dispersion of job effects in wage offers; those with completed college facing the largest dispersion. The standard deviation of the wage offer distribution ranges in the first period from 0.22 to 0.27. This implies that within 2 standard deviations, the wage of the same worker varies by ± 54 percent depending on his job.[22]

Regarding secular trends, the standard deviation of permanent wage risk increased for all workers by approximately 0.01. For those with a college degree, the rise materialized in the third period, while the increase is close to linear for the other education groups. Low skilled workers faced a substantial lower permanent risk in the 1980s. Therefore, in relative terms, lower skilled worker experience the most rise in uncertainty.

The dispersion of the wage offer distribution changed substantially for all workers. For college workers, the standard deviation increased by 0.03. Again, the rise materializes in the third period.[23] Similarly, college dropouts experienced an increase of 0.02. Similar to permanent risk, the rising uncertainty materialized already during the 1990s. Contrary to these groups, high school workers experienced a decline in the dispersion to the wage offer distribution by 0.04 in the third period. Finally, the dispersion to transitory wage shocks declines for all workers. Unfortunately, we are unable to differentiate between true transitory shock and measurement error. Consequently, the result represent a mix between the two. A falling

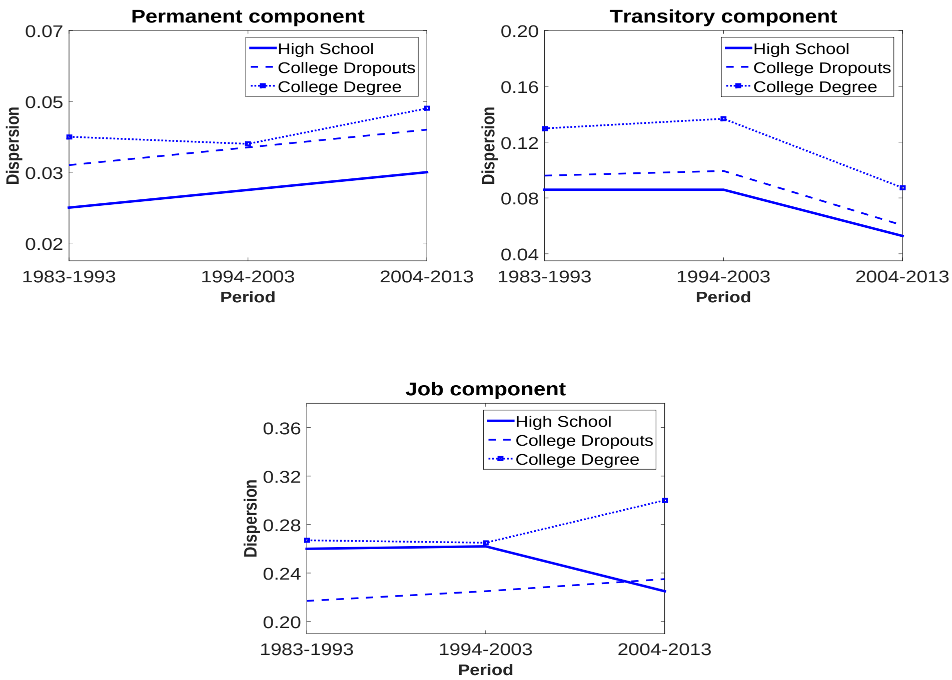
[21] We use a simplex method to find a local minimum and consider 30 different starting points to insure that we find the global minimum.

[22] Averaging over skill groups, our estimated dispersion at the wage offer distribution is similar to the one found in Hall and Mueller (2015) who identify it using information on reported reservation wages.

[23] One concern may be that a decline in spurious job to job transitions due to sample redesign leads to trends in the estimated wage offer distribution. As described in the Online Appendix, we attempt to clean the data from such transitions. Moreover, we would expect the major break occurring from the first to the second period, as data quality increased from 1990 onwards.

dispersion; therefore, may be the result of improved interviewing techniques introduced in the 1996 and 2004 survey (see Moore (2008)).

Figure 4.1. Evolution of the Wage Variance Components: Accounting for Selection

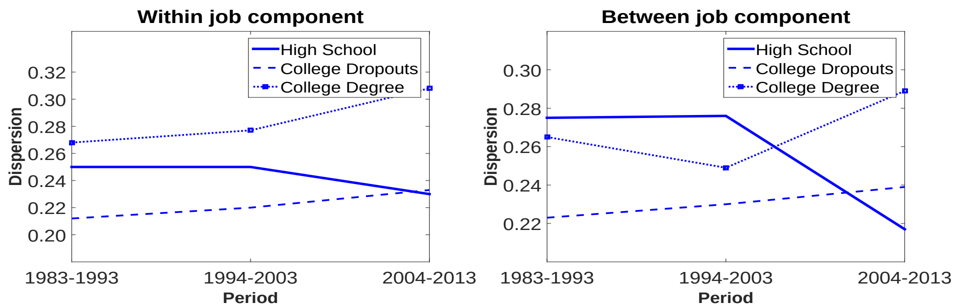


Notes: Estimation is conducted by period and education degree group. To identify the components, we use the first and second moments of wage growth, and the autocovariance function of wage growth up to lag 3. Appendix 4.A.6 provides the correlations and bootstrapped standard errors.

Appendix 4.A.6 displays the estimated selection correlations. Workers show substantial persistence in unobserved participation heterogeneity, consistent with the productivity and match component being partially unobserved. In line with this, a positive innovations to productivity increase participation. The correlation between the unobserved component of mobility and participation decisions are for most of the cases significant and positive which may suggest heterogeneity in job finding rates. The theoretical effects of shocks to human capital and mobility are ambiguous. In the first two periods, we find a negative correlation suggesting that, after a positive shock, workers are less likely to quit to non-employment to search for a new job. In the last period, the correlation becomes positive for workers with less than completed college. Put differently, after a negative shock those with completed college are more likely to change their career, but lower educated workers stay with their job. Similarly, Autor et al. (2014) find that following Chinese import penetration, low and medium skilled workers have not been able to offset wage losses, but high skilled workers mostly have offset those by switching jobs. Finally, we find that a good outside offer increases the propensity of a worker to move jobs. The model does not identify well the relationship between shocks to outside offers and participation.

Our model does not differentiate between job switches within and between occupation/industry groups. To understand the source of trends in the wage offer distribution, we extend the model allowing the wage offer distribution to be different for those who stay within the same industry and occupation (*Within*), and those who change either their occupation or industry (*Between*). Fully estimating this model is beyond the scope of this paper, and we fix the selection correlations to the ones we obtain at our baseline econometric model.[24] Figure 4.2 displays the evolution of the job component for these two groups. Regarding workers with at least some college education, the increased dispersion in the wage offer distribution results from more dispersed job offers for both within and between job switchers. For workers with at most a high school degree, the decrease in the dispersion of the job component is most pronounced for between movers. Interestingly, average wage growth from switching industries/occupations tends to increase over time for workers with at least some college education, but decreases for high school workers. Taken together with declining mobility after negative wage shocks, our results suggest that these workers face worsening opportunities from switching jobs. Whether staying in their current career, or, particularly, when moving to another industry/occupation, they are less likely to encounter a good paying job in the 2000s than in the 1980s.

Figure 4.2. Evolution of the job Component: Within vs. Between

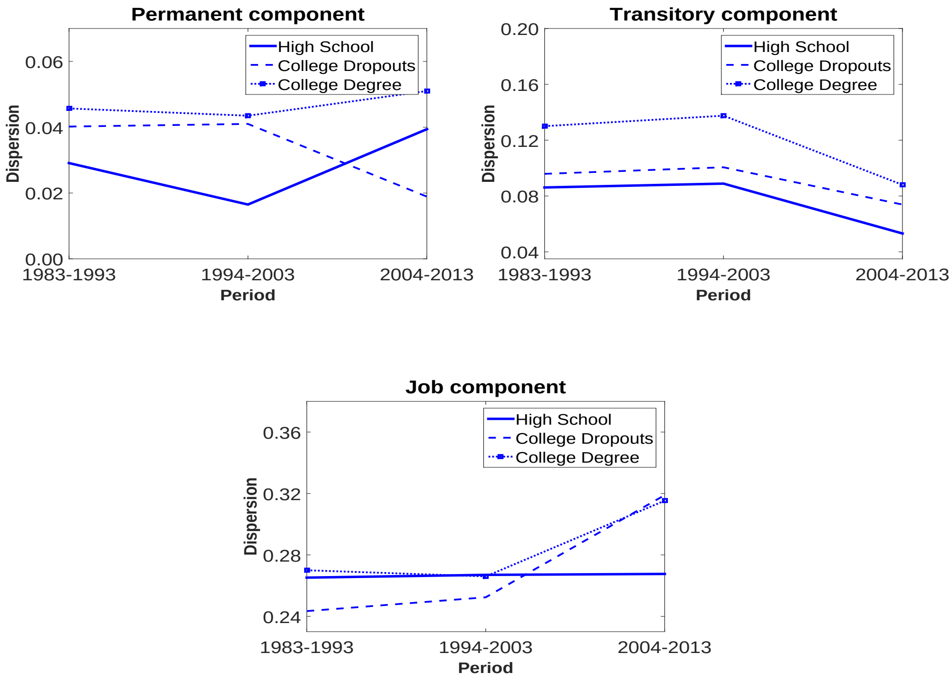


Notes: Within (Between) job component is identified through workers who stay (change) at the current industry and occupation conditional on changing the employer. Estimation is conducted by period and education degree group. To identify the components, we use the first and second moments of wage growth, and the autocovariance function of wage growth up to lag 3. Selection correlations are fixed to the estimated ones in the baseline model.

[24] This implies setting $\rho_{\xi_W \mu} = \rho_{\xi_B \mu} = \rho_{\xi \mu}$, $\rho_{\xi_W \pi} = \rho_{\xi_B \pi} = \rho_{\xi \pi}$ and $\rho_{\xi_W \pi - 1} = \rho_{\xi_B \pi - 1} = \rho_{\xi \pi - 1}$.

Finally we ask, how important is it to account for selection? Using the process for individual wages at Equation 4.1, we could identify the permanent, transitory and job component when ignoring selection, using the second moments of (uncorrected) unexplained wage growth for job stayers and movers.[25] Figure 4.3 provides the estimated components. Different from our baseline results, permanent wage risk declines by 50% for workers with some college education. Moreover, if we had ignored selection, we would have over-estimated the increase in the job component at workers with at least some college and conclude it remains flat for high school workers.

Figure 4.3. Evolution of the Wage Variance Components: Ignoring Selection



Notes: Estimation is conducted by period and education degree group. To identify the components, we make use of the second moment of (uncorrected) residual wage growth of job stayers, $(\sigma_\epsilon^2 + Var(e_{it}))$, and job movers, $(\sigma_\epsilon^2 + 2\sigma_\psi^2 + Var(e_{it}))$, and the autocovariance function up to lag 3.

[25] In specific, the variance of job stayers would be $\sigma_\epsilon^2 + Var(e_{it})$, and the variance of job movers would be $\sigma_\epsilon^2 + 2\sigma_\psi^2 + Var(e_{it})$.

4.3 The Effects of Changes in Risk on Wage Inequality and Welfare

Our empirical results identify the changes in underlying risk that workers faced over the last decades. Yet, they are silent about the quantitative consequences for wage inequality and welfare. In order to identify these effects, we develop a partial equilibrium, life-cycle incomplete-market model, consistent with the wage process and the selection mechanisms from Section 4.2.

Importantly, we explicitly model workers' insurance against risk through leisure, government insurance, and an on-the-job search technology. Our model extends the life-cycle model developed by Low et al. (2010) with job-to-job transitions resulting from reallocation shocks, which Tjaden and Wellschmied (2014) show to be important to infer the underlying distribution of workers over heterogeneous jobs.

4.3.1 Model

The economy is populated by a finite number of workers $\mathscr{I}$ who have either high school, some college, or college degree education. Time is discrete, workers live for H periods and discount the future with factor β. As in our empirical analysis, the length of a period is one quarter.

Workers spend 37 years in the labor market and another ten years in retirement. Within each quarter, workers may be employed, unemployed, disabled, or retired.[26] Importantly, we assume that financial markets are incomplete, such that workers have only access to a risk free asset a that pays returns $R = 1 + r$, and are unable to borrow, $a_{t+1} \geq 0$.

At the beginning of life, worker i draws a log human capital according to $p_{i1} \sim N(\mu_N, \sigma_N^2)$. Afterwards, human capital follows a random walk with a drift component that depends on the employment state and age:

$$p_{ih+1} = \begin{cases} p_{ih} + \nu_1 + \epsilon_{ih} & \text{if employed and} \leq 50 \text{ years} \\ p_{ih} + \nu_2 + \epsilon_{ih} & \text{if employed and} > 50 \text{ years} \\ p_{ih} - \delta + \epsilon_{ih} & \text{if unemployed,} \end{cases}$$

[26] We allow agents in the model to work for, at most, 37 years such that it coincides with the same age span we consider in our empirical analysis.

where $\epsilon_{ih} \sim N(0, \sigma_\epsilon^2)$, and h denotes the age of the worker. Wages in the data peak around age 50, and we use ν_1 and ν_2 to match this wage profile. We make use of δ to reflect skill depreciation during unemployment.

Workers search for jobs in a frictional labor market, both on and off the job. When meeting a job, they randomly draw a log job component ψ_{ij} from a normal distribution with cumulative distribution function $F(\psi)$. Consequently, gross earnings for the employed are[27]

$$w_{ih}^g = exp(p_{ih} + \psi_{ij}).$$

The government grants several programs insuring workers against low earnings. First, the earnings tax is progressive. Following Heathcote et al. (2015), earnings after taxes are given by

$$w_{ih} = \tau_c w_{ih}^{g\ \tau^p},$$

where $\tau^p < 1$ determines the progressivity of the tax code.

Furthermore, we allow workers to receive unemployment benefits for the quarter following job destruction. The benefits replace a constant fraction of worker's last quarter earnings subject to a cap:[28]

$$b_{ih} = min\{\bar{b} w_{ih-1}, b_{max}\}.$$

During the last ten working years, workers may receive disability insurance.[29] Moving to disability insurance is a permanent exit from the labor market. At its onset, disability insurance required workers to have a health condition that prohibits working, something we abstract from in our model. Autor and Duggan (2006) show that in 1984, the government greatly relaxed the eligibility criteria, which used to require workers being unable to function in a work setting, and shifted the criteria to alternative factors such as mental illness. As a result,

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[27] We abstract from intensive hours decisions and transform hourly wages from the data into earnings assuming a 40 hour workweek. Furthermore, our simulations include transitory shocks to earning but we assume to be measurement error.

[28] Legislation usually grants 26 weeks of benefits. Reducing benefits to one quarter allows us to treat it similar to a lump-sum payment to those becoming unemployed. Consequently, the benefits affect employment decisions only through a wealth effect. This assumption allows us to simplify the problem of the unemployed worker as past earnings are not part of the state space of the unemployed.

[29] By legislation, workers may apply to disability insurance throughout their working life. Yet, most people enter after the age of 50, possibly reflecting the fact that the acceptance probability rises with that age.

applications have risen substantially, particularly during recessions, and applicants have the opportunity to challenge denial of benefits with three appeal steps. We model this application procedure in such a way that benefits are only granted with probability υ. To apply for benefits, legislation requires a worker to be continuously non-employed for 5 months, and having worked before that period. To approximate this structure, the worker can only apply one quarter after becoming non-employed. Moreover, the worker may not search for a job within the same quarter of application. Benefits follow

$$S(\bar{w}_{ih}) = \begin{cases} 0.9\bar{w}_{ih} & \text{if } \bar{w}_{ih} \leq d_1 \\ 0.9d_1 + 0.32(\bar{w}_{ih} - d_1) & \text{if } d_1 < \bar{w}_{ih} \leq d_2 \\ 0.9d_1 + 0.32(d_2 - d_1) + 0.15(\bar{w}_{ih} - d_2) & \text{if } \bar{w}_{ih} > d_2, \end{cases}$$

where d_1, d_2 are bend points governing the concavity of benefits. $\bar{w}_{ih}$ are the average earnings of a worker i over his life-cycle at age h, following

$$\bar{w}_{ih+1} = \begin{cases} \frac{w_{ih}+\bar{w}_{ih}h}{h+1} & \text{if employed} \\ \frac{\bar{w}_{ih}h}{h+1} & \text{if unemployed} \\ \bar{w}_{ih} & \text{if disabled or retired.} \end{cases}$$

Consequently, concave benefits, and their dependence on past earnings, make disability insurance an attractive option for workers with poor earnings outcomes. After working life, workers receive social security benefits, which follows the same formula as disability insurance, and are fixed throughout retirement.

In addition, the government provides an universal means-tested program to all low income workers that mirrors in parts the US *Food Stamps Program*. Denote by y_i total worker gross income minus a fixed income deductible, transfers are given by

$$F_{ih}(y_{ih}) = \begin{cases} \overline{F} - 0.3y_{ih} & \text{if } y_{ih} < \underline{y}, \\ 0 & \text{otherwise .} \end{cases}$$

To summarize, total government transfers are

$$T_{ih} = \begin{cases} F_h(w^g_{ih}) & \text{if employed,} \\ F_h(b_{ih}) + b_{ih} & \text{if just became unemployed} \\ F_h(0) & \text{if unemployed,} \\ F_h(\bar{w}_{ih}) + S(\bar{w}_{ih}) & \text{if disabled,} \\ F_h(\bar{w}_{ih}) + S(\bar{w}_{ih}) & \text{if retired.} \end{cases}$$

Finally, workers derive utility from consumption and leisure. Aguiar and Hurst (2005) show that households, after exiting employment, use the additional available time to engage in home production and reduce shopping costs. To allow for this type of insurance, we choose an utility function with complementarity between consumption and work:

$$U_{ih} = \Big(\frac{c_{ih} exp(\varphi P_{ih})}{1-\eta}\Big)^{1-\eta},$$

where the resulting consumption of the worker is given by

$$c_{ih} = \begin{cases} Ra_{ih} + w_{ih} + T_{ih} - a_{ih+1} & \text{if employed,} \\ Ra_{ih} + T_{ih} - a_{ih+1} & \text{if non-employed.} \end{cases}$$

Based on this environment, we proceed with defining the value functions at each employment state. Whenever a worker is retired or disabled, he does not face uncertainty and solves, respectively, the following maximization problem:

$$\begin{aligned} \mathcal{Q}_h(a,\bar{w}) &= \max_{a'}\Big\{U + \beta \mathcal{Q}_{h+1}(a',\bar{w}')\Big\} \\ \mathcal{D}_h(a,\bar{w}) &= \max_{a'}\Big\{U + \beta \mathcal{D}_{h+1}(a',\bar{w}')\Big\}. \end{aligned}$$

The value function of an unemployed worker with the option to apply for disability is given by:

$$\mathcal{U}_h(a,p,\bar{w}) = \max_{a'}\Big\{U + \beta \Theta_h(a',p,\bar{w}')\Big\},$$

where Θ_h is the upper envelope over applying for disability insurance and searching for a job. The decision to apply for disability insurance is taken after the asset decision, but before the end of period uncertainty reveals. The worker knows that the application is denied with probability $1-\upsilon$:

$$\begin{aligned}
\Theta_h(a',p,\bar{w}') \;&\equiv\; max\Big\{\upsilon\mathscr{D}_{h+1}(a',\bar{w}') + (1-\upsilon)\int \mathscr{U}_{h+1}(a',p'|p,\bar{w}')dp' \\
&\qquad ,\int EVU_h(a',p'|p,\bar{w}')dp'\Big\}, \\
EVU_h(a',p,\bar{w}') \;&\equiv\; (1-\lambda_u)\int \mathscr{U}_{h+1}(a',p'|p,\bar{w}')dp' \\
&\quad + \lambda_u\int\int \max\Big\{\mathscr{W}_{h+1}(a',p'|p,\psi',\bar{w}'),\mathscr{U}_{h+1}(a',p'|p,\bar{w}')\Big\}dF(\psi)dp',
\end{aligned}$$

where λ_u is the job finding rate when unemployed. EVU_h is the value of search in unemployment that a worker forgoes when applying to disability insurance. The value function of an unemployed worker who is unable to apply for disability, solves the following problem

$$\mathscr{U}_h(a,p,\bar{w}) \;=\; \max_{a'}\Big\{U + \beta EVU_h(a',p,\bar{w}')\Big\}.$$

Employed workers continue to sample job offers from the same distribution as the unemployed. Searching for alternative jobs while being employed is an important insurance mechanism against poor draws from the wage offer distribution. Following Tjaden and Wellschmied (2014), we allow job to job transitions to be a result of reallocation shocks. An employed worker receives a job offer with probability λ and can in general decide to stay with his old match, or form a new one. However, with probability λ_d, his choice is between the outside offer and unemployment. Examples of the latter are temporary jobs, advanced layoff notice, or firm bankruptcy. Consequently, the value of an employed worker of age h solves

$$\begin{aligned}
\mathscr{W}_h(a,p,\psi,\bar{w}) = \max_{a'}\Big\{U_h + \beta\mathbb{E}_h\Big\{(1-\omega) \\
[(1-\lambda)\Xi + \lambda[(1-\lambda_d)\Omega_E + \lambda_d\Lambda]] + \omega\mathscr{U}_{h+1}(a',p',\bar{w}')\Big\}\Big\},
\end{aligned}$$

where we have defined the following upper envelops:

$$\begin{aligned}
\Xi \;&\equiv\; \int \max\Big\{\mathscr{W}_{h+1}(a',p'|p,\psi,\bar{w}'),\mathscr{U}_{h+1}(a',p'|p,\bar{w}')\Big\}dp' \\
\Omega_E \;&\equiv\; \int\int \max\Big\{\mathscr{W}_{h+1}(a',p'|p,\psi,\bar{w}'),\mathscr{U}_{h+1}(a',p'|p,\bar{w}'),\mathscr{W}_{h+1}(a',p'|p,\psi',\bar{w}')\Big\}dF(\psi')dp' \\
\Lambda \;&\equiv\; \int\int \max\Big\{\mathscr{W}_{h+1}(a',p'|p,\psi',\bar{w}'),\mathscr{U}_{h+1}(a',p'|p,\bar{w}')\Big\}dF(\psi')dp'.
\end{aligned}$$

An employed worker keeps his job with exogenous probability $1 - \omega$, in which case he may receive an on-the-job offer. In the case of no offer, he may decide between staying employed or quit and move into unemployment. When he receives an offer, it may be a regular offer or a reallocation shock. In the former case he decides between his current job, the outside offer, and unemployment, Ω_E. In the latter case, the set of alternatives are the new offer or unemployment, Λ.

4.3.2 Calibration

We calibrate the coefficient of relative risk aversion and the interest rate outside of our data. The former, η, is set to 1.5, consistent with Attanasio and Weber (1995). Following Siegel (2002), we fix the value of r to imply a yearly interest rate of 4%. The remaining parameters in the model are calibrated to match empirical moments of the 1980's in the United States; the first period of our empirical analysis. Most of our calibration targets are education specific. Tables 4.1 and 4.2 summarize the calibration, and Appendix 4.A.7 reports the targeted empirical moments.

We set the dispersion of the permanent shock and the dispersion of the wage offer distribution to the values estimated in our empirical section. In order to match the average amount of self-insurance present in the data, we calibrate β to target the mean wealth of the population between age 25 and 61. To calibrate the amount of insurance from leisure (φ), we target the drop in employment rates between age 45 and 61. In our framework, the utility of leisure may also capture other insurance mechanisms that we abstract from the model, such as home production, reduced shopping costs of non-employed workers, and the labor supply from other members at the household. The calibration implies that high skilled workers derive substantially more utility from non-working, but the complementarity is not large for any group.

We allow individuals to start with positive wealth at the beginning of their life. To do so, we assume that initial wealth is a random draw from the estimated empirical wealth distribution of young workers (between age 25 and 28). In addition, we set σ_N^2 to match the initial variance of log wage inequality, and μ_N, to match the average wage at the beginning of workers' life. Human capital, after the first period, follows a random walk that depends on the employment state. The terms ν_1, ν_2, and δ are calibrated to target the average wage changes from age 25 to 50 and from 51 to 61, and median wage losses from unemployment.

Given the estimated parameters of the wage process, it remains to calibrate the parameters that allows us to target the worker transition rates and the government programs. In

Table 4.1. Main Calibration

Parameter	HS	SC	C	Target
σ_ϵ	0.03	0.04	0.049	Dispersion permanent shock
σ_ψ	0.26	0.24	0.27	Dispersion job effects
σ_N	0.29	0.31	0.29	Initial wage dispersion
μ_N	7.22	7.3	7.48	Initial mean wage
r	0.01	0.01	0.01	4% annual interest rate
$(1-\beta)$%	0.59	0.54	0.44	Wealth to earnings ratio
η	1.50	1.50	1.50	Risk aversion
φ	-0.06	-0.1	-0.12	Employment drop 45-60
ν_1 %	0.46	0.61	0.71	Wage growth 25-50
ν_2 %	-0.40	-0.58	-0.76	Wage growth 51-61
δ %	1.30	0.81	1.25	Wage losses from U
ω %	1.40	0.63	0	EU flow rate
λ_u %	17.62	18.51	20.04	UE flow rate
λ %	4.06	4.01	3.77	JTJ flow rate
λ_d %	49.90	48.15	42.40	% of wage cuts upon

Notes: HS refers to workers with at most a high school diploma, while SC to college dropouts, and C to college degree. The left column states the variable, and the second, third, and fourth column state the calibrated value. EU stands for employment to unemployment, UE for unemployment to employment, JTJ for job to job movements, and U for unemployment.

Table 4.2. Calibration of Welfare State

Parameter	Value	Source
$\bar{b}$	0.70	Anderson and Meyer (1997)
$\underline{b}_{max}$	1992	Price (1985)
$\overline{F}$	680	Kerr et al. (1984)
d_1	801	Social Security Administration (2016)
d_2	4836	Social Security Administration (2016)
υ	0.43	Social Security Administration (2015)
τ^c	1.84	Tax schedule intercept
τ^p	0.89	Tax progessivity

particular, the exogenous job destruction rate, ω, is set to match the movements from employment to unemployment not explained by endogenous separation, and λ_u to match the job finding rate in the data.[30] Additionally, the information on job to job movements and accompanying wage changes identify λ and λ_d. To this end, we define job to job transitions whenever the worker reported to have been mostly employed in both quarters, and never spend time searching between the two jobs when not employed. Our identifying assumption for separating voluntary and involuntary movements consists in that the former always result in expected wage increases. Together with the losses due to stochastic idiosyncratic shocks to wage potential and transitory shocks, setting λ_d allows us to replicate the share of job to job movements resulting in nominal wage losses.

Further, we calibrate the size of the welfare state to the mid 1980's. Unemployment benefits usually last two quarters in the United States. However, in the model, they only last one quarter. To compensate, we calibrate the replacement rate to be twice the level estimated by Anderson and Meyer (1997). Moreover, we compute the maximum benefit as the average maximum benefits paid by US states.[31] We model the universal means-tested program in line with the regulations from the *Food Stamps Program* for a household composed of 4 persons. The maximum amount of benefits is calculated as the need for basic nutrition according to the *Thrifty food plan* detailed in Kerr et al. (1984). The bend points d_1 and d_2 determine the concavity of social security transfers. Social Security Administration (2016) reports the appropriate values. The probability of acceptance into disability benefits, υ, is calibrated to match the share of accepted claims between 1984 and 1993 that is reported in Social Security Administration (2015). Finally, in order to calibrate the parameters of the tax function, we estimate the following equation using the SIPP data[32]

$$ln(w_{ih}) = ln(\tau^c) + \tau^p ln(w_{ih}^g),$$

4.3.3 Model Fit

Given the specified calibration, our model is able to provide implications in regards to (untargeted) labor market outcomes. To begin with, our model predicts a decline in consumption

[30] To compute the latter, we only consider individuals who report searching for employment at least one week within the quarter.

[31] See Price (1985).

[32] We use *TAXSIM* to construct w_{ih}. Given that taxes are filled at the household level, if the household has more than one earner, we compute the individual tax as the share of the household tax according to individual earnings contributions.

after a job loss of 0.06 log points, while the available estimates from US predict a drop of less of 0.1 log points (see Chetty (2006)). The decline in consumption in our model arise due to insufficient insurance, and from complimentarity of work with consumption. The small decline in the data is; therefore, is consistent with the latter being small.[33]

Following Hornstein et al. (2012), the mean-minimum residual wage is a useful statistic to evaluate the performance of search models with heterogeneous jobs. Particularly, it allows us to assess the amount of sorting of workers over these heterogeneous jobs. The second row in the table shows that our model closely matches the data. An alternative measure to judge the amount of sorting over heterogeneous jobs are the wage dynamics conditional job to job transitions. Rows three and four compare average wage growth, conditional on positive or negative wage growth. Based on the data so as our model predictions, workers experience on average wage changes around 0.26 log points. Approximately, 50% of transitions result in wage loses, consequently, average wage gains from job to job transitions are close to zero.

Further, the excess variance of job stayers over job switchers is informative on the dispersion of the wage offer distribution. The model predicts relatively lower excess variance, particularly for college dropouts. Put differently, the statistic suggests that workers are somewhat better sorted over jobs in the model than in the data. However, the difference is small. Moreover, the model implies the correct ordering across education groups.

Table 4.3. Untargeted Moments

	All Workers-Model			All Workers-Data		
$\Delta ln(c)$ EU	-0.06			-0.10^{*}		
	HS	SC	C	HS	SC	C
Mean-min ratio	2.18	2.29	2.53	2.17	2.13	2.49
Wage gain JTJ %	29.29	24.98	29.72	28.23	25.62	30.28
Wage loss JTJ %	-30.00	-25.50	-29.77	-25.16	-26.00	-29.07
$V(\Delta w_i^b)$-$V(\Delta w_i^w)$	0.13	0.09	0.12	0.14	0.12	0.15

Notes: $-0.1*$ denotes less than -0.1 log points (in absolute value). HS refers to workers with at most a high school degree, while SC to college dropouts, and C to college degree. Data moments refer to the first period of analysis in the data: 1983-1993. *Mean-min ratio:* is the ratio between the average wage and the 5th percentile wage. $V(\Delta w_i^b)$-$V(\Delta w_i^w)$*:* is the excess variance of residual wage growth of job movers relative to job stayers.

Further, we ask whether our model is able to replicate our empirical results from Section 4.2.3. Our baseline model does not feature heterogeneity that would let us use exclusion restriction to identify selection. We discuss in Appendix 4.A.8 an extended model which fea-

[33] Indeed, Browning and Crossley (2003) and Bloemen and Stancanelli (2005) show that consumption does not drop upon unemployment for households with positive financial wealth.

tures additional workers' heterogeneity which allows us to obtain identification. The model replicates the sign of the correlation coefficients found in Section 4.2.3. Similar to our finding above, the model implies a somewhat smaller estimate for σ_ϕ.

Finally, we analyze the implications of inequality over the life cycle. The estimated earnings uncertainty, together with the labor market friction and the selection, shape wage inequality over the life-cycle. Figure 4.4 compares this cross sectional wage inequality over the life-cycle in the model relative to the data.[34] Both in model and the data, inequality increases to similar amounts over the life-cycle. However, the model implies a too steep increase early in life, and too little increase for elderly workers. The discrepancy may arise from two sources. First, the model is simulated for a cohort which is followed for the entire life-cycle, something impossible to do in the SIPP data. Consequently, our empirical estimates are based on workers with, possibly, different wage risk at different stages of their lives. Second, we get a pronounced decrease in inequality in the model at age 50 coming from the selection into disability, while we do not observe this pattern empirically. In this respect, we assume that workers may only apply to disability from age 50, while in the data workers may apply to disability earlier in life, which may also explain the relatively lower increase of inequality over the life-cycle in the data.

4.3.4 Sources of Rising Wage Inequality

To quantify how changes in underlying risk translate into changes in observed wage dispersion, we simulate our structural model with the risk parameters estimated for the 1980's and compare it to a simulation based on the risk parameters estimated for the 2000's.[35] In this experiment, changes in risk are the only difference between the two periods; the initial dispersion of workers, mean wages, and the institutional framework are unchanged.

Table 4.4 compares the changes in inequality in the model to the data. Our model can explain 84% of the increase in inequality for workers with at most some college, while we overestimate by 15% the increase in inequality at college workers. Furthermore, empirically,

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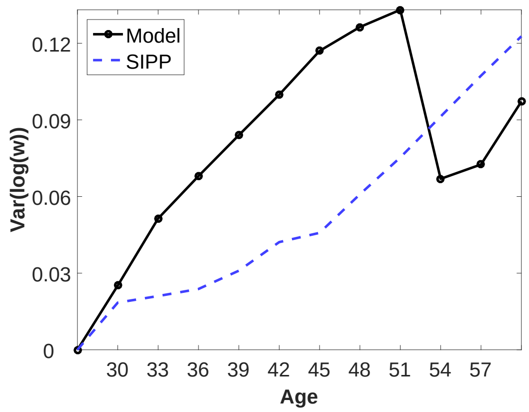
[34] We proceed with some data adjustments for the particular analysis regarding the evolution of wage inequality. To begin with, we trim the lowest 1% of observations of hourly income by educational degree. Regarding top income, the surveys censors each source of income above specified top coded levels. To account for this problem, we follow Heathcote et al. (2010b) and estimate the upper tail of the income distribution assuming it follows a Pareto distribution. Further, we replace each right-censored observation with a random draw from the fitted distribution, conditional on being larger than the top-coded threshold.

[35] We solve two separate steady states. As far as the data did not yet converge to the new steady state, our model may overestimate the role that changes in risk play.

Figure 4.4. Life Cycle Wage Profile



Notes: The figure displays the variance in yearly log hourly wage over the life cycle in the model and the SIPP. To ameliorate the effect of small amount of observations in the data, we compute the variance in log hourly wage by age bins of 5 years. All series are normalized to zero at the first age group. The data features a series of worker characteristics not present in the model. To make it comparable, we control in the data for race, region, metropolitan area, marriage, and time fixed effects.

Table 4.4. Increase of Within-Education Wage Inequality

	High School	College Dropouts	College
SIPP	0.022	0.043	0.040
Model	0.017	0.039	0.046
Model-Wage offer	-0.020	0.003	0.007

Notes: The table displays the change in the variance of residual log wages between the first and last period. *Model*: The change from model simulation based on the point estimates of risk and wage offer distribution presented in Section 4.2.3.2. *Model-Wage offer*: The change in inequality resulting from changes in the wage offer distribution only.

inequality has increased least in the group of workers with high school education, and the model is consistent with this pattern. The row labeled *Wage offer* displays changes in inequality when the dispersion of the wage offer distribution changes, and the dispersion of wage shocks remains at the level of the first period. Changes in the wage offer distribution contributed significantly to rising wage inequality for college dropouts, but little for the other skill groups.[36]

[36] An increase in the wage offer distribution and a resulting rise of wage inequality is consistent with several recent papers which find that between firm wage dispersion has increased over the last decades. This includes Barth et al. (2013) and Song et al. (2015) for the US, Mueller et al. (2015) for the UK, and Card et al. (2013) for Germany.

4.3.5 Welfare Consequences of Rising Uncertainty

To assess the welfare consequences of changing wage uncertainty we simulate the change in risk measured in the data between the first and the third period. The change in risk alters the distribution of workers over employment and jobs; thereby, the tax revenue and public expenditure. Consequently, we re-calibrate the tax rate to assure that in both periods, conditional on education, the size of the government budget remains unchanged:[37]

$$\mathscr{B} \;=\; \sum_{i=1}^{\mathscr{I}}\sum_{1}^{H} b_{ih}E_{ih}^{UI} + S(\bar{w}_{ih})E_{ih}^{S} + F_h(y_{ih})E_{ih}^{F} - \sum_{i=1}^{\mathscr{I}}\sum_{1}^{H} P_{ih}(w_{ih}^{g} - \tau_c {w_{ih}^{g}}^{\tau^p}),$$

where E_{ih}^{UI}, E_{ih}^{D}, and E_{ih}^{T} are indicators that reflect whether a person receives unemployment benefits, disability/social security insurance, and means tested transfers, respectively.

Our welfare measure is the willingness to pay in terms of life-time consumption. Let c_{ih} be the consumption of a worker of age h in the original economy, and $\hat{c}_{ih}$ be the consumption in the alternative economy. The fraction of consumption which makes the worker indifferent between being born in the two different economies solves:

$$\mathbb{E}_0 \sum_{h=1}^{H} \beta^h U(c_{ih}, P_{ih}) \;=\; \mathbb{E}_0 \sum_{h=1}^{H} \beta^h U((1+\omega)\hat{c}_{ih}, \hat{P}_{ih}), \tag{4.7}$$

We assume the initial distribution over states to be the same; thus, the willingness to pay is given by

$$\omega \;=\; \left(\frac{\mathbb{E}_0 V_1}{\mathbb{E}_0 \hat{V}_1}\right)^{\frac{1}{1-\nu}} - 1.$$

Table 4.5 shows the welfare consequences of changing uncertainty between the first and the third period. The top rows shows the willingness to pay, before uncertainty about educational status is resolved. On average, an unborn worker is willing to forgo 0.23% of life-time consumption to avoid the additional risk.

These welfare costs are not evenly distributed across education groups. The first row in Table 4.5 displays the willingness to pay after workers know their educational status. Workers with at most high school education and college dropouts are willing to pay 0.5 percent of life-time consumption to avoid the change in risk. In contrast, workers with completed college experience welfare gains from the increased uncertainty.

[37] Hence, we abstract from insurance mechanisms that may occur between education groups.

Table 4.5. Welfare Effects of Rising Uncertainty

	High School	College Dropouts	College
Total wage risk %	0.51	0.56	-0.5
Wage offer %	0.41	-0.45	-1.07
Weaker government %	1.05	1.2	1.09

Notes: *All workers*: The table displays the average willingness to pay of an unborn worker, aggregating low skilled and high skilled workers, to avoid the increase in wage risk and wage offer distribution between the 1980's and 2000's. *Total wage risk*: The willingness to pay based on changes in permanent wage risk and changes in the wage offer distribution, by skill level, between the 1980's and 2000's. *Wage offer*: The willingness to pay resulting from only changes in the wage offer distribution, by skill level, between the 1980's and 2000's. *Weaker government*: The only insurance program is one half of the original benefit level of the universal means-tested program.

To shed some light on these results, we disentangle the effects of changes in permanent wage risk, and changes in the wage offer distribution. To this end, the second row displays the welfare effects from changing the wage offer distribution but keeping permanent wage risk at its old level. All type of workers prefer a more dispersed wage offer distribution. In a search model, an increase in the wage offer dispersion creates an option value to the worker: He can always break away from particular poor matches and search to find a better match. This option value outweighs the costs of increased uncertainty. Quantitatively, the increase in dispersion is largest for workers with finished college; consequently, they gain the most. Moreover, for a given increase in dispersion, the welfare implications are largest for these workers. Increasing the standard deviation by 0.01, increases the willingness to pay by 0.32 for this group, but only by 0.12 and 0.25 for the other two groups.

Comparing total welfare changes to those where only the wage offer distribution changes, provides the net effect of changes in permanent wage risk. All workers are willing to pay to reduce this type of risk, but again, there is substantial heterogeneity. To avoid an increase of the standard deviation by 0.01, workers are willing to pay between 0.1 and 1 percent of lifetime consumption. The heterogeneity arises from the different degree of insurance resulting from self-insurance, leisure, and the government.

To evaluate the importance of the government providing insurance against increasing wage risk, the third row computes welfare changes for a hypothetical economy where there is only social security. Hence, we do not consider disability insurance nor unemployment insurance, taxes are proportional, and the maximum benefits from the universal means-tested program are reduced by 50%.[38] Comparing the results to the second row, the government plays an important role in shielding workers from rising wage uncertainty. All type of workers

[38] We allow for a low level of means-tested transfers to insure that income is always positive.

would be willing to give up substantial more life-time consumption to avoid the change in risk in this hypothetical economy.

Table 4.6. Welfare Effects of Increasing the Welfare State

	High School	College Dropouts	College
More UI %	0.31	0.39	0.54
More UM %	0.04	-0.14	-0.14
More DI %	0.55	0.53	0.58

Notes: *All workers*: The table displays the average willingness to pay of an unborn worker to avoid an increase in the welfare state financed by a 1.66 percentage point rise in average taxes. *More UI*: *Unemployment insurance*. *More UM*: Universal means-tested program. *More DI*: Increase acceptance probability of *disability insurance*.

So far, we did not address the question whether the level of governmental insurance in the 1980's was adequate to insure workers. Table 4.6 provide welfare outcomes when we increase the level of different governmental programs in this period, each financed by an incremental change of average taxes by 1.66 percentage points. Raising average and maximum benefits of unemployment insurance leads to welfare losses for all three type of workers, particularly the higher skilled. There are small welfare gains present when increasing benefits of the universal means-tested program, except for workers with at most high school education. This program has relatively weak employment disincentive effects, and it provides insurance against persistent earnings losses. Disability insurance is one of the fasted growing income support programs. Autor and Duggan (2006) show that its growth is closely linked to widening eligibility criteria, an increase in υ in our framework. The last row shows that across education groups, workers are willing to spend around 0.5% of life-time consumption to avoid the more generous eligibility requirement. Disability insurance has relatively large employment affects after age 50 in our economy. The resulting increase in the tax burden creates the large welfare losses. The finding is in contrast to Low and Pistaferri (2015) who find welfare gains of loosening eligibility requirements. One difference is that they explicitly model health status that affects acceptance probabilities. Another difference is that we infer a much smaller value for the complementarity of consumption and leisure for low skilled.[39] As a result, our model favors transfer programs that keep workers employed; such as the universal means-tested program.

[39] A further difference is that in contrast to them, average earnings is a state variable in our model which makes past earnings shocks part of the decision for disability insurance.

4.4 Conclusion

This study estimates trends in labor market risk in US for the last three decades, decomposing workers' earning risk into permanent shocks to idiosyncratic productivity, and a job specific wage component. Importantly, our approach allows us distangle exogenous fluctuations at earnings from endogenous choices in response to these shocks. Using data for males over the period 1983-2013, we find that wage risk has evolved differently across education groups over the last decades. While permanent wage risk increased by about 0.01 for all workers, heterogeneity in job offers has only risen for workers with at least some college education.

In order to quantitatively understand the implications of our empirical findings for wage inequality and welfare, we build a structural partial equilibrium model of life-time utility maximization, which is consistent with the endogenous selection mechanisms present in the data. When simulating the increase in wage risk obtained empirically, we find that the model can account for 85% of the increase in within education wage inequality in US during the last three decades.

At the same time, the welfare costs of increased uncertainty are small. Our model explicitly models government transfer programs and workers endogenously selecting into these. These very programs shield workers from most of the increase in earnings risk. In addition, workers with at least some college education, compensate the increase in productivity risk with a more dispersed wage offer distribution. Larger dispersion in the latter creates an option value to the worker: He can always terminate poor matches and search for a better match.

Our analysis focuses only on male workers and does not explicitly model joint household decisions. Yet, spousal labor participation could serve as an additional insurance mechanism against individual labor market risk. Some interesting initial approaches in this direction are Shore (2010) and Blundell et al. (2008). These studies do not make a distinction between exogenous income risk fluctuations and endogenous outcomes. Erosa et al. (2012) propose a framework to estimate shocks to spouses productivity jointly, taking into account the participation margin.

Appendix 4.A Appendix

4.A.1 Moments for the Wage Variance

To reduce notation, we drop the i and t subscripts on variables. We begin by deriving the selection term present in wage growth:

$$E[\Delta W_{is}|P_{is} = P_{is-1} = 1] = E[\Delta W_{is}|P_{is} = P_{is-1} = 1, M_{is} = 0]P(M_{is} = 0|P_{is} = P_{is-1} = 1)$$
$$+ E[\Delta W_{is}|P_{is} = P_{is-1} = 1, M_{is} = 1]P(M_{is} = 1|P_{is} = P_{is-1} = 1)$$
$$= \beta\Delta x_{is} + P(M_{is} = 0|P_{is} = P_{is-1} = 1)\Big[\frac{\rho_{\epsilon\pi}\sigma_\epsilon\phi(-z\alpha)\Phi^{21}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$- \frac{\rho_{\epsilon\mu}\sigma_\epsilon\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi\pi_{-1}\cdot\mu}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Big]$$
$$+ P(M_{is} = 1|P_{is} = P_{is-1} = 1)\Big[\sigma_\epsilon\Big[\frac{\rho_{\epsilon\pi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$+ \frac{\rho_{\epsilon\mu}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Big]$$
$$+ \sigma_\xi\Big[\frac{\rho_{\pi\xi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$+ \frac{\rho_{\mu\xi}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$+ \frac{\rho_{\pi_{-1}\xi}\phi(-z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}, \frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Big]\Big]$$
$$= \beta\Delta x_{is} + P(M_{is} = 0|P_{is} = P_{is-1} = 1)\Big[\frac{\rho_{\epsilon\pi}\sigma_\epsilon\phi(-z\alpha)\Phi^{21}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$- \frac{\rho_{\epsilon\mu}\sigma_\epsilon\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi\pi_{-1}\cdot\mu}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Big]$$
$$+ P(M_{is} = 1|P_{is} = P_{is-1} = 1)\Big[\frac{(\rho_{\epsilon\pi}\sigma_\epsilon + \rho_{\xi\pi}\sigma_\xi)\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$+ \frac{(\rho_{\epsilon\mu}\sigma_\epsilon + \rho_{\xi\mu}\sigma_\xi)\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$+ \frac{\rho_{\pi_{-1}\xi}\sigma_\xi\phi(-z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}, \frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Big]$$

where

$$\begin{aligned}
\Phi^{11}(y_1, y_2; \rho) &= \int_{y_1}^{\infty}\int_{y_2}^{\infty} \phi(x_1, x_2, \rho) dx_1 dx_2, \\
\Phi^{111}(y_1, y_2, y_3; \Omega) &= \int_{y_1}^{\infty}\int_{y_2}^{\infty}\int_{y_3}^{\infty} \phi(x_1, x_2, x_3, \Omega) dx_1 dx_2 dx_3,
\end{aligned}$$

and $\rho_{u_1 u_2 \cdot u_3}$ denotes the partial correlation of u_1 and u_2 controlling for u_3.

Given our wage model specification, we can derive the expected wage growth for job stayers and movers not explained by observable person characteristic. The expected value for the former is:

$$\begin{aligned}
E(g_{it}|P_{it} = P_{it-1} = 1, M_{it} = 0) = \frac{\rho_{\epsilon\pi}\sigma_\epsilon \phi(-z\alpha)\Phi^{21}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
- \frac{\rho_{\epsilon\mu}\sigma_\epsilon \phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi\pi_{-1}\cdot\mu}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)},
\end{aligned} \tag{4.8}$$

where

$$\begin{aligned}
\Phi^{21}(y_1, y_2; \rho) &= \int_{-\infty}^{y_1}\int_{y_2}^{\infty} \phi(x_1, x_2, \rho) dx_1 dx_2, \\
\Phi^{121}(y_1, y_2, y_3; \Omega) &= \int_{y_1}^{\infty}\int_{-\infty}^{y_2}\int_{y_3}^{\infty} \phi(x_1, x_2, x_3, \Omega) dx_1 dx_2 dx_3.
\end{aligned}$$

Economic theory would suggest that negative shocks to wage potential decrease participation. Hence, because the worker participates, his shock to ϵ could not be too negative. The first term of (4.8), simply speaking, relates the probability to participate, correcting for autocorrelation, to wage growth of job stayers, which identifies $\rho_{\epsilon\pi}$.

Similarly, the relationship between wage growth of job stayers and the probability to change jobs identifies $\rho_{\epsilon\mu}$. M_{it} may be one when the worker leaves his former job due to a poor wage potential draw. Consequently, we expect a positive relationship, i.e., a person who is likely to make a mobility, but did not do so, cannot have had a too large negative wage shock.

Further, the expected wage growth of job switchers is given by:

$$\begin{aligned}
&E(g_{it}|P_{it} = P_{it-1} = 1, M_{it} = 1) = \\
&= \sigma_\epsilon\Bigg[\frac{\rho_{\epsilon\pi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\rho_{\epsilon\mu}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Bigg] \\
&+ \sigma_\xi\Bigg[\frac{\rho_{\pi\xi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\rho_{\mu\xi}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\rho_{\pi_{-1}\xi}\phi(-z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}, \frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Bigg].
\end{aligned} \tag{4.9}$$

The parameter $\rho_{\xi\mu}$ is expected to be positive, i.e., a large positive innovation in the job component should encourage mobility. We would also think that the estimated $\rho_{\xi\pi}$ should be positive, i.e., a good outside offer increases participation. However, this variable is likely not well identified. The population of workers which identifies it are those who had a large enough negative ϵ shock to trigger quitting into non-employment, but at the same time a sufficient large positive innovation in ξ to prevent this move. These are likely to be very few.

The first moments alone identify the selection terms up to the scalars σ_ϵ and σ_ξ. To identify the standard deviations separately, we require the variance of the wage growth for job stayers and job switchers. The wage growth for job stayers is defined as

$$
\begin{aligned}
&E(g_{is}^2|P_{is} = P_{is-1} = 1, M_{is} = 0) = \sigma_\epsilon^2 \\
&- \frac{z\alpha\rho_{\epsilon\pi}^2\sigma_\epsilon^2\phi(-z\alpha)\left(\Phi^{21}\left(\frac{-\kappa\theta+\rho_{\pi\mu}z\alpha}{\sqrt{(1-\rho_{\pi\mu}^2)}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{(1-\rho_{\pi\pi_{-1}}^2)}}, \rho_{\mu\pi_{-1}\cdot\pi}\right)\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\kappa\theta\rho_{\epsilon\mu}^2\sigma_\epsilon^2\phi(-\kappa\theta)\left(\Phi^{11}\left(\frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{(1-\rho_{\mu\pi_{-1}}^2)}}, \frac{-z\alpha+\rho_{\pi\mu}\kappa\theta}{\sqrt{(1-\rho_{\pi\mu}^2)}}, \rho_{\pi\pi_{-1}\cdot\mu}\right)\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&- \frac{\rho_{\pi\epsilon}\rho_{\mu\epsilon}\sigma_\epsilon^2\phi(-z\alpha, -\kappa\theta, \rho_{\mu\pi})\left(1 - \Phi\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}\cdot\pi}^2)}}\right)\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\rho_{\pi\epsilon}^2\rho_{\mu\pi}\sigma_\epsilon^2\phi(-z\alpha, -\kappa\theta, \rho_{\mu\pi})\left(1 - \Phi\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}\cdot\pi}^2)}}\right)\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&- \frac{\rho_{\pi\epsilon}^2\rho_{\pi\pi-1}\sigma_\epsilon^2\phi(-z\alpha, -z_1\alpha, \rho_{\pi\pi_{-1}})\Phi\left(\frac{-\kappa\theta+\rho_{\pi\mu\cdot\pi_{-1}}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}z_{-1}\alpha}{\sqrt{(1-\rho_{\pi\mu}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}\cdot\pi}^2)}}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&- \frac{\rho_{\epsilon\mu}\rho_{\pi\epsilon}\sigma_\epsilon^2\phi(-z\alpha, -\kappa\theta, \rho_{\mu\pi})\left(1 - \Phi\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}\cdot\mu}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}}^2)}}\right)\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\rho_{\epsilon\mu}^2\rho_{\pi\mu}\sigma_\epsilon^2\phi(-z\alpha, -\kappa\theta, \rho_{\mu\pi})\left(1 - \Phi\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}\cdot\mu}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}}^2)}}\right)\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\rho_{\epsilon\mu}^2\rho_{\pi_{-1}\mu}\sigma_\epsilon^2\phi(-z_{-1}\alpha, -\kappa\theta, \rho_{\mu\pi_{-1}})\left(1 - \Phi\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z_{-1}\alpha+\rho_{\mu\pi\cdot\pi_{-1}}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}\cdot\mu}^2)}\sqrt{(1-\rho_{\mu\pi}^2)}}\right)\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} + Var(e_{it})
\end{aligned}
$$

where $Var(e_{it})$ refers to the variance in the transitory component. This equation makes explicit that the true variance σ_ϵ^2 is different from the one observed in the data for job stayers because the latter are a self-selected group. First, part of the true shocks are not observed as workers decide quitting into non-employment given a sufficiently large negative shocks. Second, given that the workers made no mobility, the realized shock cannot have been too negative. Third, the interaction of these two effects enters and a correction for the autocorrelation in participation decisions. The variance of wage growth of job switchers is given by:

$$
\begin{aligned}
E(g_{is}^2|P_{is} = P_{is-1} = 1, M_{is} = 1) = \sigma_\epsilon^2\Big[1 &- \frac{\rho_{\epsilon\pi}^2 z\alpha\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&- \frac{\rho_{\epsilon\mu}^2\kappa\theta\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \rho_{\pi\epsilon}\Big(\frac{\phi(-z\alpha,-\kappa\theta,\rho_{\mu\pi})\Phi^{1}\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi-1\cdot\mu}z\alpha+\rho_{\mu\pi-1\cdot\pi}\kappa\theta}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}\sqrt{1-\rho_{\mu\pi_{-1}\cdot\pi}^2}}\right)(\rho_{\mu\epsilon}-\rho_{\mu\pi}\rho_{\pi\epsilon})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-z\alpha,-z_{-1}\alpha,\rho_{\pi\pi_{-1}})\Phi^{1}\left(\frac{-\kappa\theta+\tilde{\rho}_{\mu\pi}z\alpha+\rho_{\mu\pi-1\cdot\pi}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi}^2}\sqrt{1-\rho_{\mu\pi_{-1}\cdot\pi}^2}}\right)(-\rho_{\pi\pi_{-1}}\rho_{\pi\epsilon})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \rho_{\mu\epsilon}\Big(\frac{\phi(-\kappa\theta,-z\alpha,\rho_{\mu\pi})\Phi^{1}\left(\frac{-z_{-1}\alpha+\rho_{\mu\pi-1\cdot\pi}\kappa\theta+\rho_{\pi\pi-1\cdot\mu}z\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}\sqrt{1-\rho_{\pi\pi_{-1}\cdot\mu}^2}}\right)(\rho_{\pi\epsilon}-\rho_{\mu\pi}\rho_{\mu\epsilon})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-\kappa\theta,-z_{-1}\alpha,\rho_{\mu\pi_{-1}})\Phi^{1}\left(\frac{-z\alpha+\tilde{\rho}_{\mu\pi}\kappa\theta+\rho_{\pi\pi-1\cdot\mu}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi}^2}\sqrt{1-\rho_{\pi\pi_{-1}\cdot\mu}^2}}\right)(-\rho\mu\pi_{-1}\rho_{\mu\epsilon})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big)\Big] \\
&+ \sigma_\xi^2\Big[1 - \frac{\rho_{\xi\pi}^2 z\alpha\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&- \frac{\rho_{\xi\mu}^2\kappa\theta\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&- \frac{\rho_{\xi\pi_{-1}}^2 z_{-1}\alpha\phi(z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}, \frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \rho_{\pi\xi}\Big(\frac{\phi(-z\alpha,-\kappa\theta,\rho_{\mu\pi})\Phi^{1}\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi-1\cdot\mu}z\alpha+\rho_{\mu\pi-1\cdot\pi}\kappa\theta}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}\sqrt{1-\rho_{\mu\pi_{-1}\cdot\pi}^2}}\right)(\rho_{\mu\xi}-\rho_{\mu\pi}\rho_{\pi\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-z\alpha,-z_{-1}\alpha,\rho_{\pi\pi_{-1}})\Phi^{1}\left(\frac{-\kappa\theta+\tilde{\rho}_{\mu\pi}z\alpha+\rho_{\mu\pi-1\cdot\pi}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi}^2}\sqrt{1-\rho_{\mu\pi_{-1}\cdot\pi}^2}}\right)(\rho_{\pi_{-1}\xi}-\rho_{\pi\pi_{-1}}\rho_{\pi\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big) \\
&+ \rho_{\mu\xi}\Big(\frac{\phi(-\kappa\theta,-z\alpha,\rho_{\mu\pi})\Phi^{1}\left(\frac{-z_{-1}\alpha+\tilde{\rho}_{\mu\pi-1}\kappa\theta+\rho_{\pi\pi-1\cdot\mu}z\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}\sqrt{1-\rho_{\pi\pi_{-1}\cdot\mu}^2}}\right)(\rho_{\pi\xi}-\rho_{\mu\pi}\rho_{\mu\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-\kappa\theta,-z_{-1}\alpha,\rho_{\mu\pi_{-1}})\Phi^{1}\left(\frac{-z\alpha+\tilde{\rho}_{\mu\pi}\kappa\theta+\rho_{\pi\pi-1\cdot\mu}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi}^2}\sqrt{1-\rho_{\pi\pi_{-1}\cdot\mu}^2}}\right)(\rho_{\pi_{-1}\xi}-\rho\mu\pi_{-1}\rho_{\mu\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big) \\
&+ \rho_{\pi_{-1}\xi}\Big(\frac{\phi(-z_{-1}\alpha,-z\alpha,\rho_{\pi\pi_{-1}})\Phi^{1}\left(\frac{-\kappa\theta+\rho_{\mu\pi_{-1}\cdot\pi}z_{-1}\alpha+\tilde{\rho}_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}\sqrt{1-\tilde{\rho}_{\mu\pi}^2}}\right)(\rho_{\pi\xi}-\rho_{\pi\pi_{-1}}\rho_{\pi_{-1}\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-z_{-1}\alpha,\kappa\theta,\rho_{\mu\pi_{-1}})\Phi^{1}\left(\frac{-z\alpha+\rho_{\pi\pi-1\cdot\mu}z_{-1}\alpha+\tilde{\rho}_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}\sqrt{1-\tilde{\rho}_{\mu\pi}^2}}\right)(\rho_{\mu\xi}-\rho_{\mu\pi_{-1}}\rho_{\pi_{-1}\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big)\Big] + Var(e_{it}),
\end{aligned}
$$

where the variance of the wage offer distribution is given by $\sigma^2_\phi = \frac{\sigma^2_\xi}{2}$. Regarding interpretation, a similar logic as for job stayers applies with the important difference that there is now an innovation to the job component. Regarding the latter, additional correction terms arise through its correlation to past participation decisions. The variance of the transitory component is given by

$$Var(e_{it}) \;=\; \sigma^2_i\Big[1 + (1+\chi_1)^2 + (\chi_2-\chi_1)^2 + \chi_2^2\Big].$$

We identify these process by the autocovariance function of wage growth up to lag 3. Note that σ^2_ϵ and σ^2_ξ are not part of these moments.[40]

$$Cov(g_{it}, g_{it-1}) = \sigma^2_i\Big[-(1+\chi_1) + (1+\chi_1)(\chi_2-\chi_1) - \chi_2(\chi_2-\chi_1)\Big]$$

$$Cov(g_{it}, g_{it-2}) = \sigma^2_i\Big[-(\chi_2-\chi_1) - (1+\chi_1)\chi_2\Big]$$

$$Cov(g_{it}, g_{it-3}) = \sigma^2_i\chi_2$$

4.A.2 Datasets Selection and Cleaning

In this section, we describe the dataset used in our study: Survey of Income and Program Participation (SIPP). The SIPP is conducted by the US Census Bureau. It is a longitudinal multi-panel survey, nationally representative of adults in households in the United States. The survey aims to complement the information given by CPS, providing monthly and longitudinal information on the distribution of income, wealth, employment, and program eligibility and participation in the society. Individuals are interviewed, depending on the panel, up to 14 times at four-month intervals, and are being asked about their income and work experience during the preceding four months.

Following the recommendation by the US Census Bureau, we merge the core files and the longitudinal files for the samples from 1984 to 1993 and keep only observations present in both. This assures that we use longitudinal imputation techniques in the earlier surveys consistent with the surveys after 1993. Also, following the recommendation from the US Census Bureau, we do not consider observations for which no interview was obtained. Finally, we concentrate on working-age males, aged between 25 and 61 years-old. Moreover, we do

[40] We assume $P(M_{it}=1|M_{it-1}=1, M_{it-2}=1, M_{it-3}=1, M_{it-4}=1)=0$. Estimating the transitory shock process only on job stayers gives practically the same results.

not consider individuals with missing information on education, working status, or with self-employment status.

We identify jobs by employer ID numbers. We construct hourly wages at the job level by dividing quarterly earnings at the job by the total hours worked at this firm within the quarter. As workers, in principle, could have multiple jobs within the same quarter, we define the main job as the one with the most quarterly earnings.[41] Importantly, for our purpose to identify mobility, the SIPP assigns an identifying number to each firm individual is working. This allows us to determine whenever the worker change jobs across time and his respective change in hourly wage.

The SIPP provides two possibilities to construct earnings, reported earnings and the hourly pay rate. Unfortunately, the two do not always coincide and we use for each individual the measure which yields the lowest variance of wage growth across waves. As our focus is on wage dynamics, we proceed with some adjustments to imputed values which use longitudinal information not used by the SIPP procedure.[42] Conditional on earnings being imputed in a wave, and conditional on the worker not changing his job nor the hours worked from the previous to subsequent wave, we assume that imputed earnings are the median values across waves. Further, when an individual does not provide information on the hourly rate at a wave, but does in the preceding and following wave, we use the mean hourly rate (conditional on the hourly rate to change by less than 5%), to impute the missing value. Finally, we do not consider individuals where imputed hourly rate or earnings increase by more than 30% at monthly frequency, conditional on job and hours remaining constant.

Crucial to our identification of secular trends is that sample redesign does not alter the precision to which we identify job to job transitions. Starting in the 1996 panel, the SIPP uses dependent interviewing techniques for employer names on which basis the employed ID numbers are assigned. For the panels from 1990-1993, we use the cleaned employer ID numbers from Stinson (2003) which combine the survey data with administrative records to accurately identify these changes. To avoid spurious transitions, particularly before the 1990 panel, we keep the main job constant when the main employed ID changes for one month, but is the same in the month before and after, and the individual still works at this job. Finally, we drop observations where an individual is recalled from his former employer.[43] Note that,

[41] The SIPP collects data up to two jobs for each individual at each month.

[42] In order to reduce the amount of missing values, the SIPP employs a *hot desk procedure* to impute for these observations. The procedure consist in finding a *close* match of the missing observation of a worker with respondents, based on age, race, gender, marital status, household relationship, education, among other.

[43] We think of this as workers having a special search technology not well represented by our model.

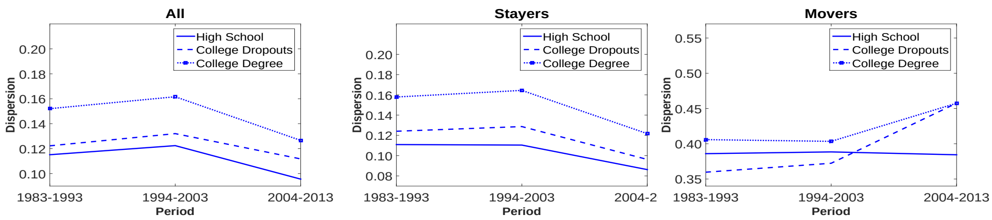
if the panels prior to 1990 suffered from spurious transitions, we would expect the dispersion of wage growth of job switchers to change from the first to the second period. This is not the case as discussed in the main text.

4.A.3 Hourly Wage Growth Dispersion

A common measure of idiosyncratic wage risk is the variance of wage growth not explained by worker observables. Figure 4.5 displays the variance of residual quarterly wage growth in the last three decades in the SIPP.[44] In line with recent administrative data from Guvenen et al. (2014), none of the education groups show an upward trend. The dispersion of wage growth peaked in the period 1993-2003, and is well below its initial level in 2004-2013.

Resulting from labor market frictions, different jobs may pay different wages to the same worker. Wage changes of workers who switch their job entail information on the presence of such job effects. We split our sample into job stayers (workers staying with the current employer) and job movers (employees switching their employer). Job stayers dominate the sample and the evolution of the variance in wage growth closely resembles the complete sample. Contrary, the variance of wage growth of job movers exhibit a positive trend, particularly after the second period, for workers with at least some college education.

Figure 4.5. Hourly Wage Growth Dispersion



Notes: The solid line is the dispersion of residual hourly wage growth for low skilled workers (high-school degree or less), while the dashed line corresponds to high skilled workers (more than high-school degree). To obtain the residual wage growth, we estimate a weighted (defined as the survey weights) regression of log hourly wage as a function of a quadratic in age and work experience, race, marital status, unemployment rate at the state level, indicators whether person lives at a metropolitan area or is disable, industry, occupations, time and region fixed effects.

[44] To obtain the residual wage growth, we estimate a weighted (defined as the survey weights) regression of log hourly wage as a function of a quadratic in age and work experience, race, marital status, unemployment rate at the state level, indicators whether person lives at a metropolitan area or is disable, industry, occupations, time and region fixed effects. Coefficients are allowed to vary by education and period.

Table 4.7. Nested Trivariate Probit: High School

	Participation (1983-1993)	**Participation** (1994-2003)	**Participation** (2004-2013)
Age	0.069***	0.045***	-0.008
Age_sq	-0.024***	-0.015***	-0.016***
UI	0.001	-0.001	-0.002**
Log(Other Income)	-0.096***	-0.086***	-0.119***
Housing	0.359***	0.261***	0.340***
Disability	-0.644***	-0.479***	-0.557***
Exper	0.246***	0.470***	0.025
Exper_sq	-0.067***	-0.102***	0.053***
Metro	0.073***	0.062***	0.114***
Married	0.361***	0.278***	0.119***
State Unemp (%)	-9.444***	-9.891***	-5.215***
White	0.527***	0.363***	0.190***
Year dummies	136.04***	26.62***	33.19***
	(10 df)	(9 df)	(9 df)
Regional dummies	26.19***	51.38***	12.20***
	(3 df)	(3 df)	(3 df)
Quarter dummies	22.47***	11.21***	33.04***
	(3 df)	(3 df)	(3 df)
Constant	1.495***	1.541***	1.612***
	Mobility (1983-1993)	**Mobility** (1994-2003)	**Mobility** (2004-2013)
Age	-0.077***	-0.055***	-0.032*
Age_sq	0.017***	-0.003	-0.000
UI	-0.002*	-0.000	-0.002
Log(Other Income)	-0.007*	0.004	0.008
Housing	-0.152***	-0.202***	-0.064
Exper	-0.330***	-0.710***	-0.300***
Exper_sq	0.086***	0.162***	0.039
Disability	0.227***	0.302***	-0.035
Metro	0.054**	0.050*	-0.050
Married	-0.042*	0.005	0.086***
State Unemp (%)	-1.304**	-1.348	-4.610***
White	0.038	-0.020	-0.026
Year dummies	150.24***	17.38**	17.00**
	(10 df)	(9 df)	(9 df)
Regional dummies	58.89***	25.53***	28.20***
	(3 df)	(3 df)	(3 df)
Quarter dummies	17.08***	7.13*	6.62*
	(3 df)	(3 df)	(3 df)
Industry dummies	243.02***	39.75***	18.09***
	(6 df)	(6 df)	(6 df)
Occupation dummies	72.76***	34.03***	28.20***
	(9 df)	(9 df)	(9 df)
Constant	-1.095***	-0.724***	-0.921***
Obs	108831	42121	26339

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance, and in parenthesis, the test constraints degrees of freedom.

4.A.4 Estimated Regressions

Table 4.8. Nested Trivariate Probit: College Dropouts

	Participation (1983-1993)	**Participation** (1994-2003)	**Participation** (2004-2013)
Age	0.032**	0.043***	-0.052***
Age_sq	-0.008	-0.029***	0.001
UI	-0.004***	-0.001	-0.001
Log(Other Income)	-0.100***	-0.105***	-0.109***
Housing	0.287***	0.335***	0.217***
Disability	-0.650***	-0.536***	-0.473***
Exper	0.219***	0.432***	0.191***
Exper_sq	-0.069***	-0.092***	0.043**
Metro	0.024	0.057	0.066**
Married	0.408***	0.202***	0.181***
State Unemp (%)	-8.791***	-10.879***	-3.642***
White	0.458***	0.282***	0.109***
Year dummies	113.04***	53.57***	59.55***
	(10 df)	(9 df)	(9 df)
Regional dummies	74.18***	21.46***	16.82***
	(3 df)	(3 df)	(3 df)
Quarter dummies	5.22	22.47***	41.02***
	(3 df)	(3 df)	(3 df)
Constant	2.144***	2.191***	1.422***
	Mobility	**Mobility**	**Mobility**
	(1983-1993)	(1994-2003)	(2004-2013)
Age	-0.086***	-0.125***	-0.061***
Age_sq	0.024**	0.043***	0.017
UI	-0.001	0.002	0.004**
Log(Other Income)	-0.000	0.008	0.005
Housing	-0.201***	-0.198***	-0.090**
Exper	-0.116*	-0.510***	-0.013
Exper_sq	0.044**	0.107***	-0.022
Disability	0.066	0.235***	0.128
Metro	0.126***	-0.112**	-0.035
Married	-0.094***	-0.047	-0.038
State Unemp (%)	0.802	-0.180	-3.042***
White	0.137***	0.038	-0.041
Year dummies	65.42***	14.74*	12.97
	(10 df)	(9 df)	(9 df)
Regional dummies	14.97***	1.80	10.48**
	(3 df)	(3 df)	(3 df)
Quarter dummies	8.58**	6.22	3.69
	(3 df)	(3 df)	(3 df)
Industry dummies	118.70***	58.54***	92.33***
	(6 df)	(6 df)	(6 df)
Occupation dummies	67.53***	42.48***	26.80***
	(9 df)	(9 df)	(9 df)
Constant	-1.325***	-0.479	-0.266
Obs	38086	21558	24455

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance, and in parenthesis, the test constraints degrees of freedom.

Table 4.9. Nested Trivariate Probit: College

	Participation (1983-1993)	**Participation** (1994-2003)	**Participation** (2004-2013)
Age	0.055***	0.066***	-0.011
Age_sq	-0.031***	-0.040***	-0.033***
UI	-0.001	-0.000	-0.001
Log(Other Income)	-0.112***	-0.113***	-0.102***
Housing	0.333***	0.257***	0.235***
Disability	-0.662***	-0.657***	-0.473***
Exper	0.289***	0.329***	0.193***
Exper_sq	-0.088***	-0.082***	0.032**
Metro	0.086***	0.098***	0.096***
Married	0.372***	0.228***	0.171***
State Unemp (%)	-6.558***	-5.306***	-3.831***
White	0.406***	0.351***	0.101***
Year dummies	146.28***	71.64***	59.39***
	(10 df)	(9 df)	(9 df)
Regional dummies	40.51***	10.26**	12.81***
	(3 df)	(3 df)	(3 df)
Quarter dummies	6.70*	6.90*	22.66***
	(3 df)	(3 df)	(3 df)
Constant	2.063***	1.874***	1.777***
	Mobility (1983-1993)	**Mobility** (1994-2003)	**Mobility** (2004-2013)
Age	-0.075***	-0.041***	-0.026
Age_sq	0.016*	-0.011	0.002
UI	-0.003**	-0.001*	-0.000
Log(Other Income)	-0.012**	-0.010	-0.015***
Housing	-0.187***	-0.181***	-0.202***
Exper	-0.139**	-0.558***	0.079
Exper_sq	0.046***	0.132***	-0.036
Disability	0.241***	0.232***	0.072
Metro	0.012	0.018	-0.052
Married	-0.102***	-0.027	0.077***
State Unemp (%)	0.652	-0.628	1.384*
White	-0.036	0.009	-0.026
Year dummies	73.81***	32.87***	40.88***
	(10 df)	(9 df)	(9 df)
Regional dummies	11.14**	13.78***	10.70**
	(3 df)	(3 df)	(3 df)
Quarter dummies	11.65***	15.41***	14.13**
	(3 df)	(3 df)	(3 df)
Industry dummies	78.12***	91.35***	58.17***
	(6 df)	(6 df)	(6 df)
Occupation dummies	94.32***	76.86***	72.33***
	(9 df)	(9 df)	(9 df)
Constant	-0.871***	-0.701**	-1.371***
Obs	67018	41350	44764

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance, and in parenthesis, the test constraints degrees of freedom.

4.A.5 Hourly Wage growth

Before we proceed with the estimation and decomposition of income risk into the permanent, transitory and job component, we proceed by removing any predictable change in wage growth such as age, marital status, education, among others. Importantly, to obtain unbiased estimates, we need to account for the selection into participation and job mobility. In Appendix 4.A.1 we derive the selection terms present in wage growth. Making use of this derivation, let us define the components to be included in the wage growth regression in order to account for the selection:

$$
\begin{aligned}
C1 &= \frac{\phi(-z\gamma)\phi(-z\gamma)\Phi^{21}(A_{12},A_{13};\rho_{\mu\pi_{-1}\cdot\pi})}{\int_{-z\gamma}^{\infty}\int_{-z_{-1}\gamma}^{\infty}\phi(x_1,x_3,\rho_{\pi\pi_{-1}})dx_1dx_3} \\
C2 &= \frac{\phi(-\kappa\theta)\Phi^{11}(A_{21},A_{23};\rho_{\pi_{-1}\pi\cdot\mu})}{\int_{-z\gamma}^{\infty}\int_{-z_{-1}\gamma}^{\infty}\phi(x_1,x_3,\rho_{\pi\pi_{-1}})dx_1dx_3} \\
C3 &= \frac{\phi(-z\gamma)\Phi^{11}(A_{12},A_{13};\rho_{\mu\pi_{-1}\cdot\pi})}{\int_{-z\gamma}^{\infty}\int_{-z_{-1}\gamma}^{\infty}\phi(x_1,x_3,\rho_{\pi\pi_{-1}})dx_1dx_3} \\
C4 &= \frac{\phi(-z_{-1}\gamma)\Phi^{11}(A_{31},A_{32};\rho_{\mu\pi\cdot\pi_{-1}})}{\int_{-z\gamma}^{\infty}\int_{-z_{-1}\gamma}^{\infty}\phi(x_1,x_3,\rho_{\pi\pi_{-1}})dx_1dx_3}
\end{aligned}
$$

where

$$\begin{aligned}
\Phi^{21}(A_{12}, A_{13}; \rho_{\mu\pi_{-1}\cdot\pi}) &= \Phi^{21}\left(\frac{-\kappa\theta + \rho_{\mu\pi} z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\pi\pi_{-1}} z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right),\\
\Phi^{11}(A_{21}, A_{23}; \rho_{\pi_{-1}\pi\cdot\mu}) &= \Phi^{11}\left(\frac{-z\alpha + \rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi\pi_{-1}\cdot\mu}\right),\\
\Phi^{11}(A_{12}, A_{13}; \rho_{\mu\pi_{-1}\cdot\pi}) &= \Phi^{11}\left(\frac{-\kappa\theta + \rho_{\mu\pi} z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\pi\pi_{-1}} z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right),\\
\Phi^{11}(A_{31}, A_{32}; \rho_{\mu\pi\cdot\pi_{-1}}) &= \Phi^{11}\left(\frac{-z\alpha + \rho_{\pi\pi_{-1}} z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}, \frac{-\kappa\theta + \rho_{\mu\pi_{-1}} z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\mu\pi\cdot\pi_{-1}}\right),\\
\Phi^{11}(y_1, y_2; \rho) &= \int_{y_1}^{\infty}\int_{y_2}^{\infty} \phi(x_1, x_2, \rho)\,dx_1 dx_2,\\
\Phi^{21}(y_1, y_2; \rho) &= \int_{-\infty}^{y_1}\int_{y_2}^{\infty} \phi(x_1, x_2, \rho)\,dx_1 dx_2.
\end{aligned}$$

4.A.6 Wage Variance Estimates

Table 4.10. Wage growth regression: High School

	Wage growth (1983-1993)	**Wage growth** (1994-2003)	**Wage growth** (2004-2013)
Age	-0.001**	-0.000	-0.001
Age_sq	0.001	0.000	0.000
Married	-0.000	-0.000	0.001
Ch. Married	0.007	0.016**	0.00
White	0.000	-0.003	-0.000
Unemp (%)	-0.066**	0.094	-0.078
Ch. Unemp (%)	0.053	0.375	0.081
Exper	-0.001	0.011	-0.011
Exper_sq	0.000	-0.002	0.0039*
Ch. Metro	0.007	0.016	0.009
Metro	0.001	-0.001	0.001
Disability	-0.000	-0.005	-0.002
Ch. Disability	-0.027	0.001	-0.012
Year dummies	2.57***	0.92	2.79***
	(10 df)	(9 df)	(9 df)
Regional dummies	0.43	0.55	0.14
	(3 df)	(3 df)	(3 df)
Ch. Regional dummies	1.94	0.92	0.58
	(3 df)	(3 df)	(3 df)
Quarter dummies	8.52***	3.81***	13.31***
	(3 df)	(3 df)	(3 df)
Industry dummies	2.93***	0.79	0.38
	(6 df)	(6 df)	(6 df)
Ch. Occupation dummies	5.80***	4.12***	1.09
	(9 df)	(9 df)	(9 df)
Ch. Industry dummies	4.77***	1.50	2.45**
	(6 df)	(6 df)	(6 df)
C1	0.009	0.014	0.004
C2	0.017	0.064	0.018
C3	0.624	0.388	-0.010
C4	-0.257	-0.917	-0.478
Constant	-0.000	-0.021	0.046*
Obs	98956	38362	22486

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance, and in parenthesis, the test constraints degrees of freedom.

Table 4.11. Wage growth regression: College Dropouts

	Wage growth (1983-1993)	**Wage growth** (1994-2003)	**Wage growth** (2004-2013)
Age	-0.001	-0.002	-0.002
Age_sq	0.001	0.001	0.001
Married	-0.001	0.004	0.003
Ch. Married	-0.002	0.010	0.013
White	0.002	0.002	0.002
Unemp (%)	-0.082*	-0.064	-0.086
Ch. Unemp (%)	-0.098	-0.861	0.236
Exper	0.005	0.008	-0.003
Exper_sq	-0.001	-0.001	0.001
Ch. Metro	0.009	0.044*	-0.008
Metro	-0.001	0.003	-0.001
Disability	0.001	-0.003	0.001
Ch. Disability	0.090*	-0.020**	-0.002
Year dummies	1.74*	1.46	3.40***
	(10 df)	(9 df)	(9 df)
Regional dummies	0.67	0.08	0.75
	(3 df)	(3 df)	(3 df)
Ch. Regional dummies	1.50	0.96	0.76
	(3 df)	(3 df)	(3 df)
Quarter dummies	1.78	8.13***	5.06***
	(3 df)	(3 df)	(3 df)
Industry dummies	0.48	0.60	0.03
	(6 df)	(6 df)	(6 df)
Ch. Occupation dummies	3.29***	2.52***	2.69***
	(9 df)	(9 df)	(9 df)
Ch. Industry dummies	5.13***	2.47**	1.25
	(6 df)	(6 df)	(6 df)
C1	0.012	0.033	-0.006
C2	0.034	0.047	-0.028
C3	-3.813***	0.273	0.206
C4	8.725**	-0.650	0.107
Constant	0.003	-0.023	0.024
Obs	35903	20346	21815

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance, and in parenthesis, the test constraints degrees of freedom.

Table 4.12. Wage growth regression: College

	Wage growth (1983-1993)	**Wage growth** (1994-2003)	**Wage growth** (2004-2013)
Age	-0.001	-0.002*	-0.002
Age_sq	0.000	0.001	0.000
Married	0.003	0.001	0.002
Ch. Married	0.032***	0.024**	0.004
White	0.004	0.005	0.004
Unemp (%)	-0.051	-0.024	-0.126**
Ch. Unemp (%)	-0.113	-0.016	0.354
Exper	0.005	0.007	-0.005
Exper_sq	-0.001	-0.002	0.002
Ch. Metro	0.009	-0.030	0.017
Metro	0.000	-0.001	0.003
Disability	-0.006	-0.005	-0.004
Ch. Disability	0.006	0.011	0.010
Year dummies	2.63***	1.00	9.10***
	(10 df)	(9 df)	(9 df)
Regional dummies	0.40	0.29	1.15
	(3 df)	(3 df)	(3 df)
Ch. Regional dummies	0.63	0.18	0.76
	(3 df)	(3 df)	(3 df)
Quarter dummies	5.25***	5.99***	12.58***
	(3 df)	(3 df)	(3 df)
Industry dummies	2.20**	0.80	0.98
	(6 df)	(6 df)	(6 df)
Ch. Occupation dummies	6.22***	3.64***	3.83***
	(9 df)	(9 df)	(9 df)
Ch. Industry dummies	4.77***	5.33***	1.16
	(6 df)	(6 df)	(6 df)
C1	-0.003	0.053	0.031
C2	0.062*	0.031	0.077
C3	0.978	-4.304	0.814
C4	-1.437	52.256*	-4.767
Constant	-0.005	0.001	0.050***
Obs	64498	39613	41890

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance, and in parenthesis, the test constraints degrees of freedom.

Table 4.13. High School

	1983-1993	1994-2003	2004-2013
Standard deviations			
σ_ϵ	0.030	0.035	0.040
	(0.004)	(0.006)	(0.008)
σ_i	0.071	0.070	0.043
	(0.002)	(0.002)	(0.004)
σ_ϕ	0.260	0.262	0.225
	(0.009)	(0.009)	(0.042)
Correlations			
$\rho_{\epsilon\pi}$	0.313	0.670	0.251
	(0.164)	(0.247)	(0.197)
$\rho_{\epsilon\mu}$	-0.358	-1.000	0.013
	(0.184)	(0.125)	(0.349)
$\rho_{\xi\pi}$	0.104	0.046	-0.342
	(0.069)	(0.047)	(0.325)
$\rho_{\xi\pi_{-1}}$	0.180	-0.030	-1.000
	(0.171)	(0.152)	(0.422)
$\rho_{\xi\mu}$	0.039	0.110	0.022
	(0.016)	(0.024)	(0.041)
$\rho_{\pi\pi_{-1}}$	0.933	0.910	0.899
	(0.002)	(0.004)	(0.004)
$\rho_{\pi\mu}$	0.496	0.394	0.141
	(0.090)	(0.130)	(0.151)
$\rho_{\pi_{-1}\mu}$	0.460	0.496	0.401
	(0.102)	(0.110)	(0.135)
MA process			
θ_1	-0.455	-0.403	-0.441
	(0.015)	(0.031)	(0.084)
θ_2	-0.049	-0.016	-0.000
	(0.017)	(0.020)	(0.032)

Notes: σ_ϵ, σ_i, σ_ϕ are the standard deviations of the permanent shock, transitory, and job respectively. Block bootstrap standard errors in parentheses (100 repetitions). We constrain all the correlation coefficients to lie between -1 and 1, and estimated θ to be negative and above -1.

Table 4.14. College Dropouts

	1983-1993	**1994-2003**	**2004-2013**
Standard deviations			
σ_ϵ	0.042	0.047	0.052
	(0.004)	(0.007)	(0.024)
σ_i	0.079	0.083	0.050
	(0.002)	(0.003)	(0.021)
σ_ϕ	0.217	0.225	0.235
	(0.030)	(0.024)	(0.058)
Correlations			
$\rho_{\epsilon\pi}$	0.078	0.805	0.378
	(0.192)	(0.229)	(0.336)
$\rho_{\epsilon\mu}$	-0.714	-0.531	1.000
	(0.167)	(0.208)	(0.481)
$\rho_{\xi\pi}$	-0.250	0.268	-0.441
	(0.234)	(0.192)	(0.539)
$\rho_{\xi\pi_{-1}}$	0.439	0.243	-0.227
	(0.512)	(0.600)	(0.414)
$\rho_{\xi\mu}$	0.111	0.128	-0.138
	(0.040)	(0.038)	(0.101)
$\rho_{\pi\pi_{-1}}$	0.926	0.901	0.907
	(0.004)	(0.007)	(0.005)
$\rho_{\pi\mu}$	0.598	0.283	0.142
	(0.152)	(0.210)	(0.200)
$\rho_{\pi_{-1}\mu}$	0.688	0.521	-0.173
	(0.142)	(0.195)	(0.206)
MA process			
θ_1	-0.433	-0.484	-0.400
	(0.019)	(0.031)	(0.204)
θ_2	-0.040	-0.086	-0.061
	(0.021)	(0.028)	(0.149)

Notes: σ_ϵ, σ_i, σ_ϕ are the standard deviations of the permanent shock, transitory, and job respectively. Block bootstrap standard errors in parentheses (100 repetitions). We constrain all the correlation coefficients to lie between -1 and 1, and estimated θ to be negative and above -1. For the period 2004-2013, we set $(\rho_{\epsilon\pi}, \rho_{\epsilon\mu}, \rho_{\xi\pi}, \rho_{\xi\pi_{-1}}, \rho_{\pi\mu})$ to the estimated correlations from period 1994-2003 due to problems to capture selection for this particular case.

Table 4.15. College Degree

	1983-1993	1994-2003	2004-2013
Standard deviations			
σ_ϵ	0.050	0.048	0.058
	(0.004)	(0.006)	(0.005)
σ_i	0.107	0.114	0.073
	(0.002)	(0.002)	(0.003)
σ_ϕ	0.267	0.265	0.300
	(0.009)	(0.022)	(0.029)
Correlations			
$\rho_{\epsilon\pi}$	0.495	0.864	0.679
	(0.220)	(0.187)	(0.143)
$\rho_{\epsilon\mu}$	-0.582	-0.168	-0.847
	(0.163)	(0.171)	(0.134)
$\rho_{\xi\pi}$	0.004	0.057	-0.131
	(0.040)	(0.159)	(0.192)
$\rho_{\xi\pi_{-1}}$	0.147	0.417	-0.953
	(0.219)	(0.234)	(0.793)
$\rho_{\xi\mu}$	0.091	0.081	0.132
	(0.022)	(0.025)	(0.029)
$\rho_{\pi\pi_{-1}}$	0.935	0.889	0.919
	(0.003)	(0.006)	(0.004)
$\rho_{\pi\mu}$	0.404	0.556	0.400
	(0.126)	(0.107)	(0.223)
$\rho_{\pi_{-1}\mu}$	0.419	0.722	0.480
	(0.138)	(0.110)	(0.290)
MA process			
θ_1	-0.435	-0.444	-0.474
	(0.016)	(0.014)	(0.032)
θ_2	-0.047	-0.097	-0.090
	(0.014)	(0.012)	(0.032)

Notes: σ_ϵ, σ_i, σ_ϕ are the standard deviations of the permanent shock, transitory, and job respectively. Block bootstrap standard errors in parentheses (100 repetitions). We constrain all the correlation coefficients to lie between -1 and 1, and estimated θ to be negative and above -1.

4.A.7 Calibration Table

Table 4.16. Calibration Targets

	High School	College dropouts	College degree
Wealth to earnings ratio	12.98	16.03	14.38
Employment drop 45-61 %	-25.49	-26.83	-30.79
Job finding %	16.48	17.52	18.25
Unemployment inflow %	2.15	1.45	0.09
Job to job %	2.82	2.78	2.30
Share wage decrease	43	43	42
Wage growth 25-50 %	35.10	54.94	74.52
Wage growth 51-61 %	-3.07	-4.78	-5.87
Wage loss U %	-11.84	-11.74	-15.58
Initial dispersion	0.38	0.38	0.41
Initial log wage	7.17	7.27	7.47

Note: The table displays the calibration targets using the SIPP data from our first period of analysis: 1983-1993. *Wealth to earnings ratio*: median of the wealth to labor income ratio. *Employment drop 45-61*: change in the participation rate at age 58-61 relative to age 45-47. *Job finding*: share of workers who are employed at the current quarter but where not employed at the previous quarter. *Unemployment inflow*: share of workers who are not employed at the current quarter but where employed at the previous quarter. *Job to job*: share of workers who changed the firm which are working across consecutive quarters. *Share wage decrease*: share of job to job transitions that implied a decrease in the hourly wage. *Wage growth 25-50*: change in the average hourly wage at age 50 relative to age 25. *Wage growth 51-61*: change in the average hourly wage at age 51 relative to age 61.*Wage loss U*: average change in hourly wage when returning back to employment. *Initial dispersion*: dispersion of log wage not explained by job effects at the beginning of workers' life (below 25 years old). *Initial log wage*: average wage at the beginning of workers' life (below 25 years old).

4.A.8 Can our Simulated Model Recover Back the Risk Components?

We would like to analyze whether our model is capable of reproducing the wage variance components found empirically. To do so, we simulate our structural model with the risk parameters estimated for the 1980's for 1,000 workers, and re-estimate the wage variance components accounting for selection into mobility and participation.

Our identification of the selection into employment and across jobs hinged on the availability of exclusion restrictions which predict employment and mobility, but do result from innovations to wages. Similar to the data, we solve the model under a high unemployment benefit regime ($b_{ih} = 1.4w_{ih-1}$) and our baseline ($b_{ih} = min\left\{0.7w_{ih-1}, b_{max}\right\}$). Our model does not feature sufficient heterogeneity to replicate the exclusion restrictions used to identify mobility in the data. Our empirical results suggest that identification for mobility results predominantly from time aggregation of workers moving away from a poor job prospect. Therefore, to identify selection into mobility, we include different degrees of job destruction rates ($90\%\omega$, ω, $110\%\omega$) together with time aggregation. Similar to the data, we simulate the model on a monthly basis and aggregate to a quarter.

Table 4.17 provides the resulting estimates of the wage variance components resulting for the simulation of this model. For simplicity, we simulate the model without measurement error. As in section 4.2.3, We estimate a nested trivariate probit as a function of a quadratic in age, experience, state of unemployment benefits and job destruction rates. The latter two variables are excluded from the wage growth equation.

Overall, we are able to recover the original estimated permanent and match component for high school and college degree workers, while we somehow over-estimate the size of the permanent shock at college dropouts. Also the selection terms implied by our model are similar to the data. As in our empirical estimation, positive innovations to productivity increase participation. Moreover, we obtain a negative correlation between shocks to productivity and unobserved heterogeneity in mobility, which suggests that workers quit to non-employment to search for a new job. Finally, we find that a good outside offer increases the propensity of a worker to move jobs.

Table 4.17. Wage Variance Components Based on Model Simulation

	High School	**College dropout**	**College degree**
Standard deviations			
σ_ϵ	0.051	0.065	0.045
σ_ϕ	0.237	0.177	0.217
Correlations			
$\rho_{\epsilon\pi}$	0.642	0.891	0.333
$\rho_{\epsilon\mu}$	-1.000	-1.000	-1.000
$\rho_{\xi\pi}$	0.023	-0.048	-0.184
$\rho_{\xi\pi_{-1}}$	-0.395	-0.280	0.331
$\rho_{\xi\mu}$	0.207	0.307	0.186
$\rho_{\pi\pi_{-1}}$	0.962	0.963	0.962
$\rho_{\pi\mu}$	0.449	0.307	0.136
$\rho_{\pi_{-1}\mu}$	0.306	0.261	0.057

Notes: σ_ϵ, σ_ϕ are the standard deviations of the permanent shock and job component shock respectively. We estimate the process based on a model simulation from the first period of analysis. We constrain all the correlation coefficients to lie between -1 and 1.

5

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