Job Creation, Job Destruction and External Financial Dependence: Theory and Evidence

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Abstract

The volatility of job flows has declined in recent decades as part of the wider phenomenon of the "great moderation" in the US. In this paper we examine whether financial deregulation and greater access to external finance may have contributed to this trend. We construct a model where greater access to credit has opposing effects on job flow volatility. On the one hand, greater access facilitates expansion of existing firms in response to favorable productivity shocks, increasing the volatility of job flows for a given distribution of shocks. On the other hand, with greater access to credit more firms can expand, which leads to an increase in aggregate demand for labor and higher wages. This offsets the response of employment to productivity shocks and reduces job flow volatility. The relationship between financial development and job flow volatility is non-monotonic. To test the relationship between volatility and access to credit we study job creation and destruction in major industrial groups in the US over the period 1973-1996, during which the economy also experienced financial deregulation. We find that industries that are initially more dependent on external finance experienced a larger decline in the volatility of job flows relative to the industries that are initially less dependent, suggesting that improved access to credit may have contributed to the decline in job flow volatility.

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1 Introduction

The decline in the volatility of US macroeconomic aggregates in recent decades has generated considerable interest among macroeconomists (Clarida, Gali, and Gertler, 2000; Stock and Watson, 2002; Davis and Kahn, 2008). We focus on one aspect of this "great moderation": employment flows in US manufacturing. In particular, we study the connections between financial deregulation and labor market flows (job creation and destruction) across major industries in the US economy over the past three decades. We argue that financial deregulation has contributed to the decline in the volatility of job flows in US manufacturing over the period 1973-1996.

The time period of the study covers years in which there have been not only major structural changes and employment reallocations in the US (Davis, Haltiwanger, and Schuh,1996; Davis, Faberman, and Haltiwanger 2006; Caballero, 2007), but also important innovations in financial markets that have affected the overall functioning of the economy. These innovations include: the greater ease with which firms and households can access credit markets (Dynan et al., 2006); the growing importance of financial intermediaries such as venture capital funds and private equity firms that focus on innovation and restructuring (Kortum and Lerner, 2000); the deregulation of the banking industry across several states in the 1980s and an associated higher rate of new business incorporations and entrepreneurial activity (Black and Strahan, 2002). At the same time, the volatility of economic activity both at the aggregate level and at the level of industries and individual firms has changed appreciably over the last few decades (Comin and Mulani, 2006; Davis, Haltiwanger, Jarmin, and Miranda, 2006). The coincident timing of these developments suggests that financial deregulation may have influenced structural changes in job creation, hiring and retention practices of firms, job security, and displacement risks.[1]

[1] Blanchard and Simon (2001) argue that the decline in output volatility began in the 1950s, was interrupted in the 1970s and early 1980s, and reappeared thereafter. Although they do not study the causes of the decline, they suggest that improvements in financial markets may have reduced investment and consumption volatility and thereby contributed to the decline in aggregate output volatility.

We develop a two-period, non-overlapping generations model with imperfect credit markets and study how the improvement in the efficiency of those markets affects job creation and job destruction. Firms face exogenous productivity shocks and rely on financial markets for liquidity to tide over the adverse shocks. The impact of deregulation on volatility depends on the initial degree of financial development. The model predicts that at a low level of financial development, deregulation of financial markets and improved access to finance can raise the volatility of job creation and job destruction, but that at higher levels of development deregulation lowers the volatility of these employment flows.

Our model provides a specific mechanism through which financial development affects an important correlate of growth - restructuring and reallocation in the manufacturing sector. As Rajan and Zingales (1998) have argued, the links between finance and growth have been difficult to pin down at a macroeconomic level, or even at a sectoral level, possibly because empirical measures of the channels through which financial development affects growth (reducing moral hazard and adverse selection, allocating capital to its most productive use, diversifying risks) are difficult to find. An alternative approach to determining how finance affects growth would be to look at outcomes in the labor market that are associated with structural change in the economy. Caballero (2007) highlights the importance of restructuring in the growth process. Here we use measures of job creation and job destruction as proxies for restructuring.

The second half of the paper confronts the predictions of our model with empirical evidence from the US. We use data from the NBER-CES Database (Bartelsman, Becker, and Gray, 2000) and the job creation and job destruction database of Davis, Haltiwanger and Schuh (1996, with subsequent updates). The results indicate that the financial deregulation that took place in US financial markets post-1985 affected the volatility of employment flows (in particular, job destruction rates) more for those industries that are ex ante more financially dependent. Specifically, we find that volatility of job destruction rates decreases to a larger degree for the initially more financially-dependent sectors. This points to a role of financial markets in moderating the volatility of job flows in the US.

Our paper relates to a large literature on the relationship between financial development and volatility. Raddatz (2006) studies industry-level data from a sample of 47 countries and shows that financial development is associated with a decline in relative output volatility of industries with higher liquidity needs. Kaminsky and Schmukler (2003), on the other hand, argue that financial development can increase volatility because the improved access to credit increases leverage in the economy. Although these results suggest that there is no consensus on the relationship between financial development and volatility, Matsuyama (2007) provides a unifying framework for reconciling these seemingly conflicting results. Matsuyama shows that macroeconomic aggregates such as the equilibrium rate of return, volatility, and inequality often respond non-monotonically to improvements in credit markets. Our model of job flows exhibits this non-monotonicity property. As we describe in more detail below, volatility of job flows increases over a certain range of improvement in credit markets before declining as credit markets improve further. Depending on the initial imperfection in credit markets, we may therefore see either an increase or a decrease in volatility of job flows following a financial liberalization / deregulation that improves firms' access to credit.

Our study also has an advantage over other studies in being able to distinguish between the effect of institutions on volatility and financial development on volatility. Since we focus on one country with relatively well-advanced institutions of economic governance at the onset of our study, further institutional development over the period of the study is not expected to be that relevant. Furthermore, unless other regulatory changes took place at the level of industries in 1985 in such a way that the effects on relative volatility of industries that are more dependent on external finance are identical to the effects of financial deregulation, our test will be able to pick up the effects of financial development on volatility of job flows.

The paper is organized as follows. The model is presented in Section 2. Section 3 discusses the data we use. The empirical specifications and results are presented in Section 4. Section 5 concludes.

2 A Model of Financial Development, Job Creation and Destruction

Environment

Consider a two period, non-overlapping generations economy. There are two types of individuals: workers of measure L and entrepreneurs of measure N. Workers supply labor inelastically. Entrepreneurs have initial (human) wealth W that they can use to start a firm. There is no borrowing for start-ups since human wealth cannot be collateralized. Final output by firm i in period 1 is

$$Y_{1i} = W\, A_1^{1-\alpha} L_{1i}^{\alpha}. \tag{1}$$

Since all entrepreneurs are ex ante identical and all of them experience the same level of productivity A_1 in the first period, they will all hire the same number of workers $\frac{L}{N}$ so that $\int_0^N L_i di = L$. First period profit π_1 (identical across all firms) is the residual claim on output after workers are paid their wages.

$$\pi_1 = (1-\alpha)\, W\, A_1^{1-\alpha} \left(\frac{L}{N}\right)^{\alpha}. \tag{2}$$

At the end of period 1, firms can approach the credit market to borrow by collateralizing their first period flow profit. However, due to credit market imperfections, not all firms can borrow. Only a fraction χ of firms can access credit markets.[2] Those that access credit markets can borrow up to m times their cash holdings (profit from period 1) at the rate r. For now, simplify by setting $r = 0$ so that all entrepreneurs who can borrow will want to do so.

Firm-level productivity shocks

At the start of period 2, firms face an exogenous productivity shock. The shock consists of both aggregate and idiosyncratic components, so that $A_{2i} = \nu_2 + \varepsilon_i$. The aggregate shock is distributed $\nu_2 \sim LN(\overline{\nu}, \sigma_v^2)$ whereas the idiosyncratic shock is distributed $\varepsilon_i \sim LN(\overline{\epsilon}, \sigma_\epsilon^2)$.

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[2] This is a reduced-form way of entering a supply (of credit) side constraint: the credit market grants credit to the first χN applicants on a sequential first-come, first-served basis while it turns away the remaining $(1-\chi)\,N$ applicants. Matsuyama (2007), p. 8, provides additional justification for this assumption.

In period 2, profits are given by

$$\pi_{2i} = \begin{cases} (W + \mu\pi_1)A_{2i}^{1-\alpha} L_{2i}^{\alpha} - w_2 L_{2i} & \text{if the firm can borrow} \\ (W + \pi_1)A_{2i}^{1-\alpha} L_{2i}^{\alpha} - w_2 L_{2i} & \text{if the firm cannot borrow} \end{cases} \tag{3}$$

where $\mu = 1 + m$ and w is the second period wage rate.

Labor Demand

The labor demand expressions consistent with profit maximization is

$$L_{2i}^{D}(w_2) = \begin{cases} A_{2i}\left(\frac{\alpha(W+\mu\pi_1)}{w_2}\right)^{\frac{1}{1-\alpha}} & \text{if the firm can borrow} \\ A_{2i}\left(\frac{\alpha(W+\pi_1)}{w_2}\right)^{\frac{1}{1-\alpha}} & \text{if the firm cannot borrow} \end{cases} \tag{4}$$

Total demand for labor is given by

$$L_2^D = \int_0^N \left[\chi A_{2i}\left(\frac{\alpha(W+\mu\pi_1)}{w_2}\right)^{\frac{1}{1-\alpha}} + (1-\chi)A_{2i}\left(\frac{\alpha\left(W+\pi_1\right)}{w_2}\right)^{\frac{1}{1-\alpha}}\right] di \tag{5}$$

which can be re-expressed as

$$L_2^D = \left(\chi\left(\frac{\alpha(W+\mu\pi_1)}{w_2}\right)^{\frac{1}{1-\alpha}} + (1-\chi)\left(\frac{\alpha(W+\pi_1)}{w_2}\right)^{\frac{1}{1-\alpha}}\right)\int_0^N A_{2i} di \tag{6}$$

$$= \left(\chi\left(\frac{\alpha(W+\mu\pi_1)}{w_2}\right)^{\frac{1}{1-\alpha}} + (1-\chi)\left(\frac{\alpha(W+\pi_1)}{w_2}\right)^{\frac{1}{1-\alpha}}\right) N\,\bar{A}_2 \tag{7}$$

where $\bar{A}_2 = \frac{1}{N}\int_0^N A_{2i} di$ is the sample average of second-period productivity (provided N is sufficiently large, by the Law of Large Numbers this will be close to the true population mean of the productivity shock taking into account both its aggregate and idiosyncratic components).

Second period wage

The equilibrium second period wage rate w_2^* clears the labor market:

$$\begin{aligned} L &= \left(\chi \left(\frac{\alpha(W+\mu\pi_1)}{w_2^*} \right)^{\frac{1}{1-\alpha}} + (1-\chi) \left(\frac{\alpha(W+\pi_1)}{w_2^*} \right)^{\frac{1}{1-\alpha}} \right) N\,\bar{A}_2 \\ (w_2^*)^{\frac{1}{1-\alpha}} &= \frac{\chi\left(\alpha(W+\mu\pi_1)\right)^{\frac{1}{1-\alpha}} + (1-\chi)\left(\alpha(W+\pi_1)\right)^{\frac{1}{1-\alpha}}}{L} N\,\bar{A}_2 \\ w_2^* &= \left[\frac{\chi\left(\alpha(W+\mu\pi_1)\right)^{\frac{1}{1-\alpha}} + (1-\chi)\left(\alpha(W+\pi_1)\right)^{\frac{1}{1-\alpha}}}{L} N\,\bar{A}_2 \right]^{1-\alpha} \end{aligned} \tag{8}$$

Second period wage w_2^* is a function of second-period mean productivity level $\bar{A}_2$, the amount of borrowing μ that can be done, and the level of financial development. In particular, the wage is increasing in the fraction of firms that get credit χ. As discussed below, the impact of financial development (through an increase in χ) on the wage rate will be important for determining the response of employment levels.

Second period employment level

Substituting for w_2^* into the labor demand equations 4 we get the second period employment levels as

$$L_{2i}^* = \begin{cases} A_{2i} \left[\frac{[\alpha(W+\mu\pi_1)]^{\frac{1}{1-\alpha}}}{\bar{A}_2\left(\chi(\alpha(W+\mu\pi_1))^{\frac{1}{1-\alpha}} + (1-\chi)(\alpha(W+\pi_1))^{\frac{1}{1-\alpha}}\right)} (L/N) \right] = A_{2i}\Psi^C = L_{2i}^C(A_{2i}) \\ \text{if the firm can borrow} \\ A_{2i} \left[\frac{[\alpha(W+\pi_1)]^{\frac{1}{1-\alpha}}}{\bar{A}_2\left(\chi(\alpha(W+\mu\pi_1))^{\frac{1}{1-\alpha}} + (1-\chi)(\alpha(W+\pi_1))^{\frac{1}{1-\alpha}}\right)} (L/N) \right] \equiv A_{2i}\Psi^{NC} = L_{2i}^{NC}(A_{2i}) \\ \text{if the firm cannot borrow} \end{cases} \tag{9}$$

where C and NC stand for credit and no credit. Note that $\Psi^C > \Psi^{NC}$. This indicates that for a given set of parameter values in Equation (9), for every A_{2i}

$$L_{2i}^C(A_{2i}) > L_{2i}^{NC}(A_{2i}).$$

In other words, the employment level associated with a given realization of the productivity shock is higher for a firm with credit than it is for a firm without credit that experiences the same draw.

Volatility of employment at the level of the individual firm

For a given distribution of shocks and a given fraction of firms with access to credit, the variance of second period employment (and hence the ex ante volatility of employment change $L_{2i}^{*}-\frac{L}{N}$) faced by an individual firm is given by

$$VarL_{2i}^{*}=Var(L_{2i}^{*}-\frac{L}{N})=\begin{cases}\left(\Psi^{C}\right)^{2}VarA_{2i} & \text{if the firm can borrow}\\ \left(\Psi^{NC}\right)^{2}VarA_{2i} & \text{if the firm cannot borrow}\end{cases} \tag{10}$$

This variance is decreasing in the the fraction of firms that get credit (Ψ^{C} and Ψ^{NC} fall with an increase in χ). In other words, as the probability of getting credit increases, there is a decline in volatility of employment at the level of the individual firm. For the economy as a whole the effect could go in either direction: while a single firm may be adjusting employment less, more firms get to do so. As a result, as we argue below, the overall effect may go either way.

2.1 Components of employment volatility: job creation and job destruction

Recall that all firms employ L/N workers in the first period. Job creation or destruction for firm i in period 2 is given by $L_{2i}^{*}-L/N$. Whether a firm creates or destroys jobs depends on the realization of productivity it faces in the second period and also on whether the firm has access to credit or not.

Productivity cutoffs

Notice from 9 that firms create jobs if their productivity shock is above a certain cutoff value:

$$L_{2i}^{*}>L/N \text{ if } A_{2i}>\frac{\bar{A}_{2}\left(\chi\left(\alpha(W+\mu\pi_{1})\right)^{\frac{1}{1-\alpha}}+(1-\chi)\left(\alpha(W+\pi_{1})\right)^{\frac{1}{1-\alpha}}\right)}{\left[\alpha\left(W+\mu\pi_{1}\right)\right]^{\frac{1}{1-\alpha}}}\text{if the firm can borrow}$$

and

$$L_{2i}^{*}>L/N \text{ if } A_{2i}>\frac{\bar{A}_{2}\left(\chi\left(\alpha(W+\mu\pi_{1})\right)^{\frac{1}{1-\alpha}}+(1-\chi)\left(\alpha(W+\pi_{1})\right)^{\frac{1}{1-\alpha}}\right)}{\left[\alpha\left(W+\pi_{1}\right)\right]^{\frac{1}{1-\alpha}}}\text{if the firm cannot borrow.}$$

Denote these cutoff values as $\tilde{A}^{C}$ (for firms with credit) and $\tilde{A}^{NC}$ (for firms without credit).

The expressions above indicate that for $0 < \chi < 1$,

$$\tilde{A}^C < \bar{A}_2 < \tilde{A}^{NC}.$$

In other words, the productivity cutoff which determines whether a firm creates or destroys jobs is higher within the set of firms that do not have access to credit.[3]

Define the parameter Θ as

$$\Theta = \left(\frac{W + \pi_1}{W + \mu\pi_1}\right)^{\frac{1}{1-\alpha}} < 1. \tag{11}$$

The cutoff values can then be simplified as

$$\tilde{A}^C = \bar{A}_2 \left(\chi \left(1 - \Theta\right) + \Theta\right), \tag{12}$$

$$\tilde{A}^{NC} = \bar{A}_2 \left(\chi \left(\frac{1}{\Theta} - 1\right) + 1\right). \tag{13}$$

Within both the set of firms with credit and the set of firms with no credit, the cutoff productivity levels that determine whether a firm creates jobs or sheds jobs in the second period depend on the mean value of the shock $\bar{A}_2$, the fraction of firms that get credit χ, and the parameter Θ.

Special cases of the productivity cutoffs

When $\chi = 0$, no firms get credit. The operative cutoff is

$$\tilde{A}^{NC} = \bar{A}_2 \left(\chi \left(\frac{1}{\Theta} - 1\right) + 1\right) = \bar{A}_2.$$

Firms with productivity shocks $A_{2i} > \bar{A}_2$ create jobs, whereas firms with productivity shocks $A_{2i} < \bar{A}_2$ shed jobs.

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[3] Note that since $\alpha(W + \pi_1) < \alpha(W + \mu\pi_1)$, for $0 < \chi < 1$ we have the following inequality:

$$\left[\alpha\left(W + \pi_1\right)\right]^{\frac{1}{1-\alpha}} < \left(\chi\left(\alpha(W + \mu\pi_1)\right)^{\frac{1}{1-\alpha}} + (1-\chi)\left(\alpha(W + \pi_1)\right)^{\frac{1}{1-\alpha}}\right) < \left[\alpha\left(W + \mu\pi_1\right)\right]^{\frac{1}{1-\alpha}}.$$

This implies that the productivity cutoff for firms that can borrow, $\tilde{A}^C$, is less than $\bar{A}_2$ for $0 < \chi < 1$:

$$\tilde{A}^C = \frac{\bar{A}_2\left(\chi\left(\alpha(W + \mu\pi_1)\right)^{\frac{1}{1-\alpha}} + (1-\chi)\left(\alpha(W + \pi_1)\right)^{\frac{1}{1-\alpha}}\right)}{\left[\alpha\left(W + \mu\pi_1\right)\right]^{\frac{1}{1-\alpha}}} < \bar{A}_2,$$

whereas the productivity cutoff for firms that cannot borrow, $\tilde{A}^{NC}$, is greater than $\bar{A}_2$ for $0 < \chi < 1$:

$$\tilde{A}^{NC} = \frac{\bar{A}_2\left(\chi\left(\alpha(W + \mu\pi_1)\right)^{\frac{1}{1-\alpha}} + (1-\chi)\left(\alpha(W + \pi_1)\right)^{\frac{1}{1-\alpha}}\right)}{\left[\alpha\left(W + \pi_1\right)\right]^{\frac{1}{1-\alpha}}} > \bar{A}_2.$$

When $\chi = 1$, all firms get credit. The operative cutoff is

$$\tilde{A}^C = \bar{A}_2 (\chi (1 - \Theta) + \Theta) = \bar{A}_2.$$

Again firms with productivity shocks $A_{2i} > \bar{A}_2$ create jobs, whereas firms with productivity shocks $A_{2i} < \bar{A}_2$ shed jobs.

When firms can only borrow upto their first period cashflow (i.e. $m = 0; \mu = 1 + m = 1$), from Equation (11) we see that $\Theta = 1$. In this case, the cutoffs are identical:

$$\tilde{A}^C = \bar{A}_2 = \tilde{A}^{NC}.$$

Within both the set of firms with credit and the set of firms with no credit, firms with productivity shocks $A_{2i} > \bar{A}_2$ create jobs, whereas firms with productivity shocks $A_{2i} < \bar{A}_2$ shed jobs.

The employment response of a firm to productivity shocks in the second period therefore depends on whether or not the firm has access to credit, and also on the value of the shock it faces relative to the relevant cutoff. As credit markets improve and more firms get access to credit, the employment volatility responds because of a combination of changes in the wage rate across the economy and in the level of the cutoffs within both groups of firms.

2.2 The impact of credit market development on employment volatility

When credit markets improve and a larger fraction of firms get credit (χ increases), the wage rate, labor demand and the productivity cut-offs are affected. We treat the improvements in credit markets as exogenous to employment volatility at the level of the individual firm since the developments in financial markets that we document in the introduction have all taken place at a more aggregate level in response to changes in financial market policy.

Since the number of firms with access to credit increases, this shifts out the aggregate demand for labor. As Equation (8) indicates, the second period wage rate increases. Within both the group of firms with credit and the group without credit, from Equation (9) it is clear that labor demand per firm falls relative to the case where only a small fraction of firms gets credit. In other words, holding fixed the distribution of the productivity shocks, employment for every A_{2i} drops in both subsets when credit markets improve:

$$L_{2i}^{C}(A_{2i},\chi_{_L}) > L_{2i}^{C}(A_{2i},\chi_{_H}), \text{ and}$$

$$L_{2i}^{NC}(A_{2i},\chi_{_L}) > L_{2i}^{NC}(A_{2i},\chi_{_H}),$$

where $\chi_{_H} > \chi_{_L}$.

The improvement in credit markets also raises the threshold level of productivity which determines whether a firm creates or destroys jobs in the second period. From Equations (12) and (13) we have that

$$\frac{d\tilde{A}^{C}}{d\chi} = \bar{A}_2\left(1-\Theta\right) > 0, \text{ and}$$
$$\frac{d\tilde{A}^{NC}}{d\chi} = \bar{A}_2\left(\frac{1}{\Theta}-1\right) > 0.$$

The increase in the threshold levels of productivity indicates that firms must experience relatively large realizations of productivity in order to expand employment.

The overall response of employment volatility to improvements in credit markets is influenced by two competing effects. Consider the ex ante volatility of employment in the two subsets of firms as being two points on a volatility scale with $\left(\Psi^{C}\right)^2 VarA_{2i} > \left(\Psi^{NC}\right)^2 VarA_{2i}$ (as seen from Equation 10). The firms that have access to credit face a higher ex ante volatility of employment than firms that do not have access to credit. On the one hand, as χ increases a larger number of firms is in the group that faces the higher end of the volatility scale, $\left(\Psi^{C}\right)^2 VarA_{2i}$. On the other hand, as χ increases the volatility of employment at both ends of the scale declines. Which of the two competing effects dominates ultimately depends on the relevant parameter values. In general, the relationship between credit-market development and volatility of employment is non-monotonic. Simulations of our model indicate that the relationship has an inverted U-shape.

In summary, greater access to credit facilitates expansion of existing firms in response to favorable productivity shocks. This increases the volatility of job flows for a given distribution of shocks. However, with greater access to credit more firms can potentially expand and this leads to higher level of labor demand and higher wages. The increase in wages off-sets the response of employment to productivity shocks and reduces job flow volatility.

2.3 Simulation

Figure 1 shows a numerical example using log-normal distributions for the idiosyncratic and aggregate shocks. Figure 2 shows the importance of the wage effect. The dashed line represents the (log) volatility of job creation in a sector where wages are held fixed. This eliminates the effect of credit on wages, which as we argued above, tends to reduce the volatility of job flows. In line with the argument, eliminating this effect leads to a monotonic increasing relationship between access to credit and volatility.

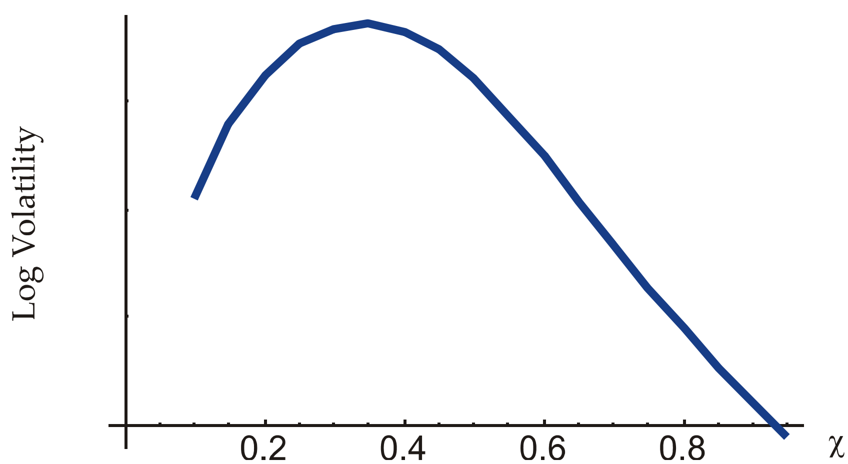

Figure 1: Volatility and Financial Development

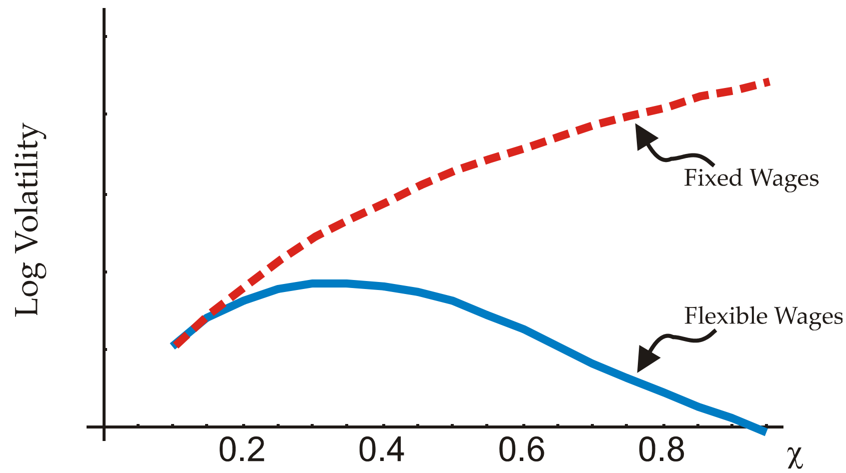

Figure 2: Wage Effect

3 Data

The main prediction of the model developed above is that improvement of financial markets can, if the initial state of development of these markets is high enough, reduce the volatility of job flows. We have also established that if initial access to credit is weak, or if wages are inflexible, such improvements can also increase volatility. Given the reduction of job flow volatility over the last two decades and the financial deregulation that has taken place at the same time, we examine whether greater availability of credit contributed to the phenomenon of lower job flow volatility. Although our model predicts a non-monotonic relationship between financial development and volatility of job flows, ultimately, however, it is an empirical question and this section attempts to shed light on it. Our approach is of the simple difference-in-differences type. We look at the reduction in volatility (and means) of job flows after 1985, which we take as the onset of the "financial revolution" (more on this below). We compare the change in volatility between two groups of industries – those that rely heavily on external finance and those that do not.

3.1 Job Flow Data

We use the measures of job creation and job destruction proposed by Davis, Haltiwanger, and Schuh (1996). These measures are constructed from the US Census Bureau's Longitudinal Research Database (LRD). The LRD contains data on US manufacturing plants with five or more employees and is available at quarterly and annual frequencies. The LRD is a panel dataset that covers roughly two-thirds of US manufacturing employment (Davis, Haltiwanger, and Schuh, 1996, p. 14). The data we use is the updated version covering 1973-1998, described in Foster, Haltiwanger and Kim (2006). The industries included in our sample are: Textile Mill Products, Apparel, Lumber and Wood Products, Furniture and Fixtures, Paper and Allied Products, Printing and Publishing, Chemicals and Allied Products, Petroleum and Coal Products, Rubber and Plastics, Leather and Leather Products, Stone, Clay and Glass Products, Primary Metal Industries, Fabricated Metal Products, Industrial Machinery and Equipment, Electronic and Electrical Equipment, Transportation Equipment, Instruments and Related Products, Miscellaneous Manufacturing Industries.[4]

Using plant-level information, Davis et al. (1996) calculate average job creation and destruction rates for each 2-digit SIC industry as follows. Job creation (JC) is defined as the sum of employment growth at all expanding units, including start-ups. Job destruction (JD) is defined as the negative of the sum of employment losses at all contracting units, including shut-downs. The plant-level employment growth rate at plant p in industry i in the year t is defined as the change in employment from year $t-1$ to year t divided by the average employment level for those two adjacent years,

$$g_{pit} = \frac{E_{pit} - E_{pit-1}}{\frac{1}{2}\left(E_{pit} + E_{pit-1}\right)}$$

The employment share of plant p in industry i in the year t is defined as

$$Z_{pit} = \frac{\frac{1}{2}\left(E_{pit} + E_{pit-1}\right)}{\frac{1}{2}\left(E_{it} + E_{it-1}\right)}$$

[4] The dataset covers twenty 2-digit SIC code industries. Foster et al. (2006) combine Food and Kindred Products (code 20) and Tobacco Products (code 21) together in the calculation of the job creation from startups, job creation from continuers, job destruction from shutdowns, and job destruction from continuers.

At the 4-digit level, however, all industry sub-groups in the 20 and 21 two-digit categories are included separately.

	Mean ($*10^{-2}$)	Variance ($*10^{-4}$)
Job Creation Rate (Overall)	8.88	4.18
Job Creation Rate (Continuing)	7.46	2.95
Job Creation Rate (Start-ups)	1.41	0.51
Job Destruction Rate (Overall)	10.08	7.84
Job Destruction Rate (Continuing)	7.77	4.93
Job Destruction Rate (Shut-down)	2.31	1.22

Table 1: Descriptive Statistics. Sample extends over 1973-1996 and covers all two-digit SIC industries except 20 and 21. Mean and Variance weighted by industry employment share for each year, and then averaged over all years.

Finally, the job creation rate is calculated as the average employment growth rate for all expanding units, weighted by their share in industry employment

$$JC_{it} = \sum_{p \in i^+} Z_{pit} g_{pit}$$

where i^+ is the subset of industry i that covers all expanding plants. Similarly, the job destruction rate is calculated as

$$JD_{it} = \sum_{p \in i^-} Z_{pit} \left| g_{pit} \right|$$

where i^- is the subset of industry i that covers all contracting plants.[5]

The descriptive statistics for the various employment flow measures are listed in Table 1. The mean and variance are weighted using employment shares.

In terms of our model, we do not distinguish between plants and firms. The employment growth rate for firm i is given by

$$g_i = \frac{\left| L_{2i}^* - L/N \right|}{\left(L_{2i}^* + L/N \right)/2}.$$

Aggregating across all expanding firms and using the weighting procedure of Davis et al. (1996), we have the following expressions for the Job Creation rate and Job Destruction

[5] Additional material on the calculation of these growth rates is available in Foster, Haltiwanger and Kim (2006). The discussion here is based on their Section 2.2

rate, respectively

$$JC = \sum_{i \in i^+} \left[\frac{(L_{2i}^* + L/N)/2}{L} \right] \left[\frac{L_{2i}^* - L/N}{(L_{2i}^* + L/N)/2} \right] = \frac{1}{L} \sum_{i \in i^+} (L_{2i}^* - L/N)$$

and

$$JD = \sum_{i \in i^-} \left[\frac{(L_{2i}^* + L/N)/2}{L} \right] \left[\frac{|L_{2i}^* - L/N|}{(L_{2i}^* + L/N)/2} \right] = \frac{1}{L} \sum_{i \in i^-} |L_{2i}^* - L/N|$$

Note that $\sum_{i \in i^+} (L_{2i}^* - L/N)$ and $\sum_{i \in i^-} |L_{2i}^* - L/N|$ are the aggregate job creation and job destruction, summing over the firm-level job creation and job destruction rates discussed in Section 2. Applying the definition of Davis et al. (1996), in the model the job creation and job destruction rates are proportional to the aggregate job creation and job destruction respectively. The factor of proportionality is $\frac{1}{L}$, the inverse of the size of the labor force. With a constant labor force, the volatility of the job creation rate and the job destruction rate is proportional to the volatility of aggregate job creation and job destruction respectively. As discussed above, the relationship between credit market development and the volatility of employment flows (of which the two components are aggregate job creation and aggregate job destruction) is predicted to be non-monotonic. The intuition carries over to the relationship between credit market development and the volatility of the job creation and job destruction rates since, as we have demonstrated here, in the model they are proportional to the volatility of aggregate job creation and aggregate job destruction.

3.2 Financial Dependence

Our measure of financial dependence comes from Rajan and Zingales (1998), who calculate the industry's demand for external financing as determined by the technology of production used in that industry. The industry's need for external finance is defined as the difference between the total investment expenditure incurred and the amount of that investment financed by internal cash. Industries differ according to the initial scale of operations and set-up costs, the duration between initiation of the project and the time when the project begins to generate revenue, and the need for ongoing investment in working capital as the project proceeds to fruition. We use their measure calculated for the 1970s as the initial external dependence and divide our sample of two digit industries into two subsets (high and low dependence), divided at the median financial dependence measure.

We follow Dynan et al. (2006) in using 1985Q1 as the start of the treatment period for financial deregulation. They document the policy reforms in financial markets that began in the 1980s with the phasing out of the Federal Reserve's Regulation Q which had placed ceilings on interest rates at depository banking institutions. Dynan et al. argue that financial innovation contributed to the stabilizing of economic activity in the period starting in 1985Q1. Here, we examine whether the effect was greater for industries that were initially more dependent on external finance.

4 Results

We first present results from a linear specification of job flow volatility. We then present results from a specification that simultaneously estimates the mean and variance of job flows.

4.1 Linear Specification

We compare the difference in volatility of job flows before 1985 versus after for the group of less dependent industries with this difference for the more dependent industries. We run the following specification

$$\sigma_{it} = \alpha + \beta_1 Dereg_t + \beta_2 Depend_i + \beta_3 \left(Dereg * Depend\right)_{it} + \epsilon_{it}$$

where σ_{it} is the standard deviation of job flows (job creation and job destruction rates) in industry i in period t, *Dereg* is a dummy that takes on the value 1 after 1985, t takes on two values (1973-1985; 1986-1998), *Depend* is a dummy that takes on the value 1 if the industry i has a Rajan-Zingales external dependence measure greater than the median in 1970.

In this specification, the coefficient β_1 represents the difference in mean volatility after 1985 compared to before for the less dependent industries, whereas β_1+ β_3 represents the difference in mean volatility after 1985 compared to before for the more dependent industries. The key coefficient is β_3, which provides the difference-in-differences comparison between the two groups of industries and indicates whether the change in volatility experienced by the more dependent industries after 1985 was significantly different from the change experienced by the less dependent industries.

	Creat.	Creat. Cont.	Creat. Start	Destr.	Destr. Cont.	Destr. Shut.
Fin.Dereg.	-0.934***	-1.231***	0.265***	-1.357***	-1.398***	0.011
	(0.209)	(0.173)	(0.066)	(0.345)	(0.324)	(0.102)
Dependence	3.315*	2.873**	0.535	4.803**	4.761**	0.372
	(1.558)	(1.056)	(0.510)	(1.885)	(1.901)	(0.608)
Fin.Dereg.xDepend	-2.093*	-1.793*	0.005	-3.960**	-4.382**	-0.391
	(1.157)	(0.989)	(0.352)	(1.604)	(1.581)	(0.552)
Constant	2.567***	2.433***	0.595***	3.716***	3.213***	0.981***
	(0.244)	(0.197)	(0.081)	(0.359)	(0.366)	(0.111)
R^2	0.464	0.622	0.062	0.401	0.444	-0.111
N	28	28	28	28	28	28

Table 2: Linear model. Significance levels: * 10%,** 5% and *** 1%. Errors clustered by industry.

The results are reported in Table 2. The dependent variable in each specification is listed at the head of the column. We first examine the volatility of overall job creation rates (Column 1). The specifications using job creation rates among continuing units and start-ups are then reported separately in Columns 2 and 3. The next column reports the specification using the volatility of the overall job destruction rate as the dependent variable. The final two columns (5 & 6) split the volatility of job destruction rates into continuing units and shutdowns.

As the first row of results in Table 2 indicates, the volatility of almost all categories of job flows fell after 1985 within the group of less dependent industries. The only exceptions are the job creation rate for start-ups and the job destruction rate for shutdowns. As the third row indicates, the volatility fell even more for the more dependent industries after 1985. The coefficient on the interaction term is negative and significant at the 10% level in the case of the volatility of the overall job creation rate. It is negative and significant at the 5% level for the volatility of overall job destruction rate. These results indicate that the more dependent industries were affected to a larger extent by financial deregulation.

We also run this specification controlling for average job flow in the period. As the results in Table 3 indicate, the volatility of overall job destruction rate fell by more for the dependent industries than for the less dependent industries after 1985. This is significant at the 5%. The significance on the interaction term in the specifications with the volatility of overall job creation rate as the dependent variable (Column 1) drops, but the sign continues to be negative. The level of average job flow is significant in all the specifications except for the volatility of the job creation rate for continuing units.

	Creat.	Creat. Cont.	Creat. Start	Destr.	Destr. Cont.	Destr. Shut.
Fin.Dereg.	-0.745***	-1.024***	0.125**	-1.314***	-1.288***	-0.012
	(0.229)	(0.236)	(0.049)	(0.317)	(0.267)	(0.095)
Dependence	1.741	1.721	-0.127	3.797**	3.293**	0.075
	(1.405)	(1.183)	(0.194)	(1.750)	(1.462)	(0.461)
Fin.Dereg.xDepend	-1.517	-1.300	0.020	-3.804**	-4.050***	-0.421
	(1.205)	(1.025)	(0.367)	(1.413)	(1.330)	(0.433)
Average Flow	0.211**	0.183	0.576***	0.179*	0.333**	0.243***
	(0.093)	(0.119)	(0.062)	(0.085)	(0.115)	(0.051)
Constant	0.738	1.077	-0.119	1.904*	0.648	0.392**
	(0.871)	(0.945)	(0.086)	(1.024)	(1.002)	(0.155)
R^2	0.610	0.671	0.841	0.481	0.557	0.403
N	28	28	28	28	28	28

Table 3: Linear model controlling for average flows. Significance levels: * 10%,** 5% and *** 1%.

4.2 Nonlinear Heteroscedasticity Model

We also estimate the relationship between job flows and financial deregulation using a model of heteroskedasticity (since our main focus is on job flow volatility) where we simultaneously model the mean and the variance of the job flows. In the first specification, in both the mean and variance equations we include the binary variables *Dereg* and *Depend* as well as their interaction.

$$y_{it} = \alpha + \gamma t + \beta_1 Dereg_t + \beta_2 Depend_i + \beta_3 Dereg \times Depend_{it} + \epsilon_{it} \qquad \text{(Mean)}$$

$$\log(Var(\epsilon_{it})) = \eta_0 + \eta_1 Dereg_t + \eta_2 Depend_i + \eta_3 Dereg \times Depend_{it} \qquad \text{(Variance)}$$

In the second specification we replace the financial dependence dummy with industry fixed effects. Here, the industry fixed effect captures all time-invariant influences on job flows (including financial dependence), whereas the interaction term reflects the differential effects of financial deregulation on job flows depending on the degree of external financial dependence.

$$y_{it} = \alpha + \gamma t + \mu_i + \beta_1 Dereg_t + \beta_2 Dereg \times Depend_{it} + \epsilon_{it} \quad \text{(Mean)}$$

$$\log(Var(\epsilon_{it})) = \eta_0 + \eta_1 Dereg_t + \eta_2 Depend_i + \eta_3 Dereg \times Depend_{it} \quad \text{(Variance)}$$

	Creat.	Creat. Cont.	Creat. Start	Destr.	Destr. Cont.	Destr. Shut.
Linear						
Fin.Dereg.	-1.828***	-1.546***	-0.140	0.239	0.241	0.122
	(0.597)	(0.479)	(0.205)	(0.893)	(0.647)	(0.336)
Dependence	6.267***	5.210***	1.010***	4.547**	3.217*	1.194*
	(1.542)	(1.373)	(0.386)	(1.999)	(1.652)	(0.656)
Fin.Dereg.xDepend	-1.642	-1.530	-0.128	0.206	0.326	0.251
	(1.926)	(1.628)	(0.613)	(2.589)	(2.013)	(0.949)
Trend	0.079*	0.034	0.033**	-0.042	-0.051	-0.002
	(0.043)	(0.034)	(0.015)	(0.065)	(0.046)	(0.025)
Constant	2.501	4.788*	-1.320	13.442***	11.733***	2.603
	(3.390)	(2.673)	(1.175)	(5.149)	(3.641)	(1.954)
Variance						
Fin.Dereg.	-0.479***	-0.780***	0.396**	-0.399**	-0.741***	0.040
	(0.164)	(0.164)	(0.164)	(0.175)	(0.171)	(0.175)
Dependence	1.514**	1.517**	1.833***	2.113***	2.345***	2.096***
	(0.647)	(0.672)	(0.640)	(0.679)	(0.679)	(0.681)
Fin.Dereg.xDepend	-1.259	-1.770*	0.147	-2.161**	-3.139***	-1.168
	(0.930)	(0.964)	(0.911)	(1.055)	(1.009)	(1.067)
Constant	2.208***	1.960***	-0.404***	2.892***	2.501***	0.695***
	(0.116)	(0.117)	(0.116)	(0.121)	(0.119)	(0.120)
Log.L	-810.8	-741.9	-457.2	-933.4	-837.1	-607.5
N	334	334	334	334	334	334

Table 4: No fixed effects. Significance levels: * 10%,** 5% and *** 1%.

The results of the first specification are presented in Table 4. The top panel of Table 4 reports the results for the means while the bottom panel reports the results for the variance. The dependent variable for each specification is listed in the column heading; the order of

	Creat.	Creat. Cont.	Creat. Start	Destr.	Destr. Cont.	Destr. Shut.
Linear						
Fin.Dereg.	-1.883***	-1.510***	-0.086	1.060	0.583	0.181
	(0.449)	(0.373)	(0.168)	(0.686)	(0.541)	(0.250)
Fin.Dereg.xDepend	-2.334	-2.182*	-0.122	-0.094	-0.327	0.183
	(1.449)	(1.299)	(0.510)	(2.130)	(1.804)	(0.697)
Trend	0.083***	0.031	0.028**	-0.113**	-0.079**	-0.008
	(0.032)	(0.026)	(0.012)	(0.049)	(0.038)	(0.019)
Constant	2.828	5.893***	-1.061	23.434***	16.403***	4.906***
	(2.544)	(2.045)	(0.975)	(3.975)	(3.047)	(1.493)
Variance						
Fin.Dereg.	-0.947***	-1.333***	0.655***	-0.979***	-1.162***	-0.038
	(0.166)	(0.167)	(0.168)	(0.180)	(0.173)	(0.189)
Dependence	2.029***	1.960***	1.530**	2.443***	2.721***	0.989
	(0.608)	(0.633)	(0.649)	(0.642)	(0.637)	(0.687)
Fin.Dereg.xDepend	-1.011	-0.757	0.214	-1.842*	-2.569***	-0.900
	(0.923)	(0.979)	(0.920)	(0.971)	(0.938)	(1.049)
Constant	1.898***	1.768***	-0.922***	2.667***	2.368***	0.090
	(0.116)	(0.117)	(0.118)	(0.122)	(0.120)	(0.126)
Log.L	-725.6	-671.9	-390.0	-851.5	-785.6	-491.0
N	334	334	334	334	334	334

Table 5: With fixed effects in top panel. Significance levels: * 10%,** 5% and *** 1%.

columns is identical to the order described above for Tables 2 and 3.

The results in the top panel indicate that the job creation rate has on average been lower after 1985 within the group of less dependent industries (row 1), while financially dependent industries had both higher job creation and job destruction rates than less dependent industries during the pre-1985 period (row 2). Furthermore, comparing across pre-1985 and post-1985 periods, the difference in average job creation and job destruction rates between less dependent and more dependent industries has not been affected significantly by the greater availability of credit since 1985.

The key results from the point of view of our theory, however, are those on the variance, reported in the bottom panel. The first row indicates that volatility fell after 1985 in almost all categories of job flows within the group of less dependent industries (row 1). The exceptions are the volatility of the job creation rate for start-ups (the only category where volatility increased significantly after 1985) and the volatility of the job destruction rate for shutdowns. As the third row indicates, the estimated coefficient on the interaction term is negative (except for the case of creation by startups) and, in most cases significant. For the volatility of the overall job destruction rate, the coefficient on the interaction term is significant at the 5% level. The effect is even stronger for the job destruction rate for continuing units (the coefficient on the interaction term is significant at the 1% level). These coefficients are economically significant as well, representing 27.5% of the variance of the overall job destruction rate and 63.7% of the variance of the job destruction rate for continuing units (the variances are reported in Table 1). This result is consistent with the hypothesis that financial deregulation affects job flow volatility to a greater extent for the financially dependent industries.

The results of the second specification are presented in Table 5. They are similar to the results of the first specification. In the bottom panel of the table, the coefficient on the interaction term continues to be significant (at the 10% level) for the volatility of the job destruction rate, indicating that the volatility of the overall job destruction rate declined to a greater extent in the post-1985 period for the more financially dependent industries. The effect is even stronger in the case of job destruction rates calculated using only the plants that continue in operation (column 5). The absolute value of the coefficient on the interaction term in this case is equivalent to 52.1% of the variance of the job destruction rate for continuing units. Furthermore, as the first row of the bottom panel of the table indicates, financial deregulation was associated with a reduction in volatility across all measures of job flows within the less dependent industries except for job creation rates calculated using only the startups, where volatility is higher in the post-1985 period relative to the years in the pre-1985 period. This effect is significant in all specifications except the last one which uses the job destruction rates of shutdowns.

4.3 Robustness

A competing hypothesis to financial innovation is one put forward by Clarida, Gali, and Gertler (2000). They argue that improvements in monetary policy have contributed to the moderation in aggregate economic activity. Improvements in monetary policy are also likely to disproportionately benefit the more financially dependent sectors of the economy since firms in those sectors are possibly affected to a larger extent by how financial markets respond to changes in monetary policy. If predicting the course of monetary policy becomes easier, firms can possibly manage their credit lines more efficiently and this change is likely to have a larger impact on the operations of firms in sectors that are more dependent on credit markets to begin with.

In order to address this competing hypothesis, we repeat the regressions reported above using an alternative division point that coincides with changes in monetary policy documented by Davis and Kahn (2008). We run the regressions using 1983 as the division year (when the Federal Reserve switched from targeting non-borrowed reserves to targeting the Federal Funds Rate). We also ran similar specifications using an earlier division point, 1979. As Davis and Kahn (2008) point out, the Fed switched from targeting the Federal Funds Rate to targeting the non-borrowed reserves in the banking system that year. Since the results are similar, we do not report them here.

We first run the following specification:

$$\sigma_{it} = \alpha + \beta_1 Post_t + \beta_2 Depend_i + \beta_3 \left(Post * Depend\right)_{it} + \epsilon_{it}$$

where, as before, σ_{it} is the standard deviation of job flows (job creation and job destruction rates) in industry i in period t, $Post$ is a dummy that takes on the value 1 after 1983, t takes on two values (1973-1983; 1984-1998), $Depend$ is the binary variable used above to capture industry financial dependence.

As the results in Table 6 indicate, within the group of less dependent industries (row 1), volatility of job flows is significantly lower post-1983 in the case of the job creation rate for

	Creat.	Creat. Cont.	Creat. Start	Destr.	Destr. Cont.	Destr. Shut.
Post	-0.389	-0.579**	0.329***	-1.101*	-1.167**	0.134
	(0.235)	(0.226)	(0.095)	(0.538)	(0.432)	(0.157)
Dependence	3.051**	2.398**	0.714	2.939*	3.295**	-0.348
	(1.337)	(0.880)	(0.557)	(1.460)	(1.354)	(0.762)
Post x Depend	0.104	0.286	0.027	0.434	0.047	0.312
	(0.404)	(0.357)	(0.215)	(0.923)	(0.840)	(0.293)
Constant	2.346***	2.209***	0.496***	3.547***	3.158***	0.819***
	(0.167)	(0.162)	(0.063)	(0.309)	(0.311)	(0.107)
R^2	0.368	0.415	0.181	0.226	0.281	0.065
N	28	28	28	28	28	28

Table 6: Linear model, break in 1983. Significance levels: * 10%,** 5% and *** 1%. Errors clustered by industry.

continuing units (at the 5% level), the overall job destruction rate (at the 10% level), and the job destruction rate for continuing units (5% level). The volatility of the job creation rate for start-ups within the group of less dependent industries increases post-1983. More important, the interaction term is not significant in any of the specifications, indicating that the change in monetary policy regime did not affect the more dependent industries in a different way than it affected the less dependent industries. Compared to similar specifications estimated using 1985 as the division year (Table 2), the results using 1983 as the division year suggest that rather than the change in monetary policy it was financial innovation that affected the more dependent industries to a greater extent than it did the less dependent industries.

We also estimate the specification controlling for average job flows in the different categories. The results reported in Table 7 are similar. The change in monetary policy that occurred in 1983 did not affect the volatility of more dependent industries to a greater degree than the less dependent industries: the interaction term is not significant in any of the specifications (row 3).

	Creat.	Creat. Cont.	Creat. Start	Destr.	Destr. Cont.	Destr. Shut.
Post	-0.347	-0.501**	0.149**	-1.141**	-1.117***	0.033
	(0.203)	(0.226)	(0.053)	(0.444)	(0.316)	(0.120)
Dependence	1.734	1.529	0.010	1.794	1.625	-0.740
	(1.172)	(1.017)	(0.237)	(1.087)	(0.966)	(0.621)
Post x Depend	0.084	0.291	-0.058	0.389	0.000	0.281
	(0.416)	(0.366)	(0.089)	(0.836)	(0.714)	(0.228)
Average Flow	0.178*	0.141	0.569***	0.175*	0.331**	0.263***
	(0.100)	(0.122)	(0.056)	(0.094)	(0.130)	(0.050)
Constant	0.889	1.213	-0.141*	1.851*	0.678	0.242*
	(0.858)	(0.905)	(0.065)	(1.042)	(1.087)	(0.132)
R^2	0.482	0.445	0.911	0.306	0.394	0.598
N	28	28	28	28	28	28

Table 7: Linear model, break in 1983, controlling for average flows. Significance levels: * 10%,** 5% and *** 1%.

In addition, we also estimate the nonlinear heteroskedasticity specification simultaneously for mean and variance of job flows using 1983 as the division year:

$$\begin{aligned} y_{it} =& \alpha + \gamma t + \beta_1 Post_t + \beta_2 Depend_i + \beta_3 \left(Post \times Depend\right)_{it} + \epsilon_{it} \\ \log(Var(\epsilon_{it})) =& \eta_0 + \eta_1 Post_t + \eta_2 Depend_i + \eta_3 \left(Post \times Depend\right)_{it} \end{aligned}$$

The results are reported in Table 8. As the bottom panel shows, the key interaction term is once again not significant in any of the specifications. Compared with the specifications estimated using 1985 as the division year, unlike financial deregulation, the change in monetary policy implemented by the Federal Reserve starting in 1983 did not have a significantly different impact on the more dependent industries than the less dependent industries (as indicated by comparing the change in volatility post-1983 relative to pre-1983 for the more dependent industries with this change for the less dependent industries).

4.4 Disaggregated data

The Rajan-Zingales measure of financial dependence is calculated at the SIC 2-digit level. In order to examine whether the relationships we find above hold at a more disaggregated level, we need alternative measures of financial dependence at the 4-digit level. Using the NBER-CES Database (Bartelsman, Becker, and Gray, 2000), we construct financial dependence

	Creat.	Creat. Cont.	Creat. Start	Destr.	Destr. Cont.	Destr. Shut.
Linear						
Post	0.511	0.314	0.327	1.526*	0.415	1.114***
	(0.634)	(0.528)	(0.209)	(0.888)	(0.678)	(0.325)
Dependence	3.679***	2.992***	0.655*	2.004	0.891	0.872
	(1.319)	(1.142)	(0.347)	(1.783)	(1.436)	(0.582)
Post x Depend	1.143**	0.844*	0.300	1.583**	1.310**	0.346
	(0.551)	(0.460)	(0.187)	(0.749)	(0.575)	(0.279)
Trend	-0.107**	-0.111***	-0.006	-0.154**	-0.088**	-0.070***
	(0.042)	(0.035)	(0.015)	(0.060)	(0.044)	(0.022)
Constant	16.727***	15.872***	1.577	21.837***	14.495***	7.658***
	(3.308)	(2.725)	(1.129)	(4.670)	(3.465)	(1.746)
Variance						
Post	-0.212	-0.378*	0.492**	-0.223	-0.537**	0.242
	(0.231)	(0.225)	(0.232)	(0.210)	(0.215)	(0.213)
Dependence	0.855	0.856	1.626**	1.916***	1.776***	1.861***
	(0.664)	(0.674)	(0.634)	(0.649)	(0.646)	(0.665)
Post x Depend	0.313	0.300	0.319	-0.277	-0.191	-0.066
	(0.290)	(0.287)	(0.279)	(0.259)	(0.264)	(0.261)
Constant	2.044***	1.797***	-0.621***	2.863***	2.513***	0.516***
	(0.133)	(0.131)	(0.135)	(0.130)	(0.130)	(0.130)
Log.L						
N	334	334	334	334	334	334

Table 8: No fixed effects, break in 1983. Significance levels: * 10%,** 5% and *** 1%.

measures for short-term financial needs at the 4-digit level (which we refer to here as a subgroup to simplify exposition). The NBER-CES data extends over 1958-1996. It includes, among a large number of variables at the subgroup level, measures of industry value-added, employment, value of materials, energy usage, investment, inventories, shipments, TFP, and payroll. We calculate the ratio of material cost / value shipments for each subgroup and use the median of this subgroup-specific ratio over the period 1958-1970 as our measure of dependence. The ratio indicates the fraction of material cost that can be covered by the value of current shipments. As before, subgroups with dependence measures greater than the median are classified as financially dependent.

Foster et al. (2006) report overall job creation and job destruction rates at the subgroup

	Without Fixed Effects Creat.	Destr.	With Fixed Effects Creat.	Destr.
Linear				
Fin.Dereg.	1.469**	0.344	1.148*	-0.497
	(0.639)	(0.456)	(0.613)	(0.451)
Dependence	0.501	1.448***		
	(0.419)	(0.558)		
Fin.Dereg.xDepend	-1.797*	-1.885***	0.217	-0.766
	(1.061)	(0.663)	(0.969)	(0.610)
Trend	-0.137***	0.004	-0.131***	-0.000
	(0.017)	(0.019)	(0.021)	(0.021)
Constant	18.858***	8.866***	19.449***	10.120***
	(1.957)	(1.943)	(1.640)	(1.688)
Variance				
Fin.Dereg.	2.321***	-0.077	1.992***	-0.047
	(0.073)	(0.075)	(0.073)	(0.074)
Dependence	0.876***	0.044	0.774***	0.019
	(0.107)	(0.110)	(0.107)	(0.108)
Fin.Dereg.xDepend	-0.299**	-0.338***	-0.188	-0.244**
	(0.120)	(0.121)	(0.120)	(0.120)
Constant	2.472***	3.815***	2.909***	4.027***
	(0.063)	(0.065)	(0.063)	(0.064)
Log.L	-34997.9	-32883.2	-36195.0	-34106.2
N	10067	10067	10067	10067

Table 9: 4-digit level regressions. Significance levels: * 10%,** 5% and *** 1%.

level over the period 1973-1998.[6] We match the two datasets to get a total of 459 subgroups. We estimate the heteroskedasticity model with and without subgroup fixed effects in the linear component (i.e. the equation for the mean job flow). As the first row of the bottom panel of results indicates, in contrast with the 2-digit specifications, the volatility of the overall job creation rate increased within the less dependent subgroups after 1985.[7] The volatility of the overall job destruction rate within the less dependent subgroups is lower after 1985, but the effect is not significant. However, the interaction term is negative and

[6] Job creation and job destruction rates are not broken down into continuing, start-ups, and shutdowns at the 4-digit level in the dataset.

[7] The increase in volatility at a finer level of disaggregated data is consistent with the finding of Comin and Mulani (2006) who report an increase in idiosyncratic risk at the level of the firm. Although the trend in volatility goes in the operate direction to that reported at the 2-digit level, one way of reconciling the divergent trends is to note that the covariance of output and employment at the 4-digit level may have gone down since the mid-1980s.

significant in all specifications other than the volatility of the job creation rate estimated with fixed effects included in the equation for the mean (column 3). The results suggest that the more financially dependent subgroups saw a less pronounced increase in volatility of job flows in the era of financial deregulation. The volatility of the overall job creation rate did not increase by as much for the more dependent subgroups as it did for the less dependent subgroups, a result which is qualitatively similar to the ones we find at the 2-digit level. Furthermore, financial deregulation had a larger negative impact on the volatility of the overall job destruction rate for the more dependent subgroups.

An additional point suggested by these results at the 4-digit level is that the influence of luck (Stock and Watson, 2002) in moderating economic activity in recent times appears to be less relevant than would be indicated by analysis at a higher level of aggregation. Since the volatility of job creation was higher after 1985 than before for the less dependent subgroups, firms in those subgroups appear to have experienced more variable shocks than was the case previously.

5 Conclusion

Job creation and job destruction reflect the shifting of employment opportunities across industries and regions. The reallocation of jobs and labor market flows of workers are related to fluctuations in economic activity that have potentially important consequences for the pace of restructuring and productivity growth. From the perspective of workers, the shifting of employment opportunities are directly connected to issues of employment security and job displacement risk.

In this paper, we study the impact of financial deregulation and external financial dependence on industry-level job flows. The volatility of job flows – job creation and job destruction – has declined in recent decades as part of the wider phenomenon of the so-called great moderation. At the same time, financial deregulation and innovations in capital markets have eased the access to finance for businesses. We examine whether financial deregulation and greater access to external finance may have contributed to the downward trend in the volatility of job flows.

We construct a model where greater access to credit has opposing effects on job flow volatility. On the one hand, greater access facilitates expansion of existing firms in response to favorable productivity shocks, thereby increasing the volatility of job flows for a given distribution of shocks. On the other hand, the fact that with greater access to credit more firms expand leads to a higher level of labor demand and higher wages. This offsets the response of employment to productivity shocks and reduces job flow volatility. The relationship between financial development and job flow volatility is non-monotonic because one effect dominates at low levels of development, whereas the other dominates at high levels of development. To test the relationship between volatility and access to credit we study job creation and destruction in major industrial groups in the US over the period 1973-1996. We find that industries that are initially more dependent on external finance experienced a larger decline in the volatility of job flows relative to the industries that are initially less dependent, suggesting that improved access to credit contributed to the decline in job flow volatility.

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