

Labor-Technology Substitution: Implications for Asset Pricing

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Abstract

This paper studies the asset pricing implications of a firm's option to adopt labor-saving technologies that replace routine-task labor with machines. I develop a model that shows it is less costly for a firm to exercise this option when productivity is low. Hence, firms with routine-task labor have an option that hedges their value against unfavorable macroeconomic shocks and lowers their exposure to systematic risk. Using establishment occupational data from the Bureau of Labor Statistics, I construct a measure of firms' share of routine-task labor. Consistent with my model's predictions, I find that in the cross-section, firms with a higher share of routine-task labor (i) invest more in machines and reduce disproportionately more of their routine-task labor during economic downturns, and (ii) have lower expected equity returns.

JEL Classification: E22, E23, G12, J24

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As technology evolves, machines tend to replace labor in certain jobs. Historical examples from the Industrial Revolution include the spinning jenny and the automatic loom replacing hand labor. More recent examples include calculators, word processors, automatic tellers, and robotic arms replacing large numbers of workers in procedural and rule-based jobs, i.e., *routine-task labor*.¹ Prior literature shows that the disappearance of routine-task jobs tends to occur during recessions rather than expansions, and that such job disappearance constitutes almost all job loss in the three most recent recessions.² This evidence suggests that labor-technology substitution is an economically important decision that varies with the business cycle.

In this paper, I explore the asset pricing implications of labor-technology substitution. Specifically, I examine whether the option for a firm to replace routine-task labor with machines is a source of macroeconomic risk that is priced in the cross-section of stock returns. I document that firms with a high share of routine-task labor have 3.1% lower stock returns per year than their industry peers with a low share. The key insight of my explanation hinges on that replacing routine-task labor with machines interrupts production. Firms thus optimally undertake such replacement when productivity is low. Hence, if the economy experiences a negative shock, firms with more routine-task labor can better improve their value through undertaking the replacement, making them less exposed to systematic risk. In line with this insight, I find that in response to an unfavorable GDP shock, firms with a high share of routine-task labor reduce investment in machines less than their industry peers but increase layoffs of their routine-task labor more than their industry peers.

To capture the economic mechanism, I develop a production-based model. In the model, a firm generates cash flows from two substitutable groups of projects. One group uses machines to perform routine tasks (*automated projects*) while the other uses routine-task labor (*unautomated projects*). Because machines are cheaper to use than routine-task labor, unautomated projects embed a switching option to become automated. A key assumption is that adopting machines takes time as the firm needs to adapt the technology embodied in the machines to

¹Examples of routine-task labor over the past 30 years include clerks, travel agents, production line assemblers, bank tellers, and tax preparers. Throughout this paper, I use machines to refer to both equipment and software.

²Jaimovich and Siu (2014) show that in the 1990, 2001, and 2008-09 recessions, routine-task jobs, which account for about half of the total employment, constitute 89%, 91%, and 94% of all job loss, respectively. The authors also show that essentially all job loss in routine-task occupations occurs in recessions and is not recovered after the recessions.

its project.³ During this adoption period, the project generates zero output. To minimize the production loss, the firm switches a project from unautomated to automated only when the project is generating low cash flows. Hence, if the economy experiences a negative shock, firms with a high share of routine-task labor (and more unautomated projects) can better improve their value by reducing future production costs through technology switching. As a result, these firms have lower exposure to systematic risk and hence lower expected returns.⁴

To study the empirical relation between routine-task labor and the cross-section of stock returns, I construct a new measure of share of routine-task labor (*RShare*) at the firm level using microdata from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics. The OES microdata provide occupational employment and wages for 1.2 million establishments in the U.S. over three-year cycles, covering 62% of total national employment. Following the labor economics literature, I first assign to each occupation a routine-task intensity score, which is calculated based on the Dictionary of Occupational Titles.⁵ I then sort all workers in each year by their occupations' routine-task intensity scores and classify the workers that fall in the top quintile of the distribution as routine-task labor. By classifying routine-task labor each year, this measure accounts for technological evolution. In particular, it accounts for the fact that certain previously non-substitutable occupations become substitutable by machines over time. A firm's *RShare* is given as the ratio of the total wages paid to its routine-task labor relative to its total wage expense. I rank firms based on their *RShare* relative to their industry peers, since different industries' production technologies may require different intensities of routine-task input to non-routine-task input.

My measure of firms' share of routine-task labor is correlated with a number of firm characteristics in a manner that is consistent with my model. In the data, high-*RShare* firms

³This assumption is proposed by literature on the slow diffusion of new technology. For instance, in the New Economy Handbook, [Hall and Khan \(2003\)](#) point out that: “[...] the costs (of adopting a new technology), especially those of the non-pecuniary ‘learning’ type, are typically incurred at the time of adoption and cannot be recovered. There may be an ongoing fee for using some types of new technology, but typically it is much less than the full initial cost.”

⁴A concrete example is Harley-Davidson Inc. In April 2009, the midst of the Great Recession, Harley-Davidson launched a comprehensive restructuring after demand for its products plummeted. The restructuring resulted in layoffs of more than 2,000 staff and production workers as well as investments in cutting-edge manufacturing equipment such as automated guided carriers. After the restructuring, the company's unlevered equity beta increased from 1.08 in the three years prior to the Great Recession (2005-2007) to 1.49 in the three years after the recession (2010-2012).

⁵See, for example, [Autor, Levy, and Murnane \(2003\)](#), [Autor, Katz, and Kearney \(2006\)](#), [Acemoglu and Autor \(2011\)](#), [Philippon and Reshef \(2013\)](#), [Autor and Dorn \(2013\)](#), [Autor, Dorn, and Hanson \(2013\)](#), and [Autor, Dorn, and Hanson \(2015\)](#).

have significantly lower ratios of machines to capital and machines to routine-task labor than their industry peers with low *RShare*. These relations are consistent with the model assumption that routine-task labor and machines are substitutes. High-*RShare* firms also have higher operating leverage, which is consistent with the model assumption that routine-task labor is more costly to use than machines.⁶ Finally, High-*RShare* firms have higher cash flows. This is consistent with the model implication that firms that experience higher cash flows are less likely to replace their routine-task labor with machines.

The main empirical findings in this paper are twofold. First, I find that, in response to unfavorable aggregate shocks, high-*RShare* firms replace more of their routine-task labor with machines than do low-*RShare* firms. Specifically, I find that high-*RShare* firms reduce both routine-task labor and *RShare* in their establishments more than their industry peers do when GDP growth is low.⁷ The reduction in *RShare* for high-*RShare* firms' establishments suggests that high-*RShare* firms not only downsize their production in bad times, but also change their production structure through the bad times. I control for state-year fixed effects in these establishment-level tests. Hence, state labor protection laws, such as wrongful-discharge laws, or state unionization laws, such as right-to-work laws, do not seem to drive the results. In addition, even though aggregate investment is procyclical, I find that in the cross-section, high-*RShare* firms reduce investment in machines significantly less than their industry peers when GDP growth is negative. Together, these results support the model's channel that high-*RShare* firms have more switching options to hedge against unfavorable aggregate shocks than low-*RShare* firms. To further support the relation between machines and routine-task labor, I run a placebo test in which I examine investment in capital other than machines. I do not find that high-*RShare* firms respond to GDP shocks differently than low-*RShare* firms in terms of investment in other capital.

Second, I find strong negative relations between firms' *RShare* and their exposure to systematic risk and expected returns. I investigate the market betas from both the conditional and unconditional specifications of the Capital Asset Pricing Model (CAPM). I find that sorting portfolios of firms by *RShare* within industry generates a monotonically decreasing pattern in both conditional and unconditional market betas. The betas of the high-*RShare*

⁶The operating leverage channel predicts that firms with a high share of routine-task labor have higher exposure to systematic risk. In Section I, I simulate the model with economically sensible parameters and find that the switching options channel dominates the operating leverage channel in predicting expected returns.

⁷I conduct this test at the establishment level instead of the firm level due to data limitations. See Section III for more details.

quintile portfolio are more than 20% lower than those of the low-*RShare* quintile portfolio in both the conditional and unconditional CAPMs. I further examine expected returns and alphas of the five portfolios and find a monotonically decreasing pattern in average excess returns but no relation between alphas and *RShare* quintiles, indicating that excess returns are explained by market betas. Comparing the high and low *RShare* quintile portfolios yields a negative return spread of -3.1% per year.⁸ This low risk premia for high-*RShare* firms is a robust feature of the data. Using both panel regressions and Fama-MacBeth cross-sectional regressions (Fama and MacBeth (1973)), I show that *RShare* consistently and negatively predicts firms' conditional betas (Lewellen and Nagel (2006)) and future excess returns after controlling for known predictors of firm risk and returns. In particular, the results are robust to controlling for firms' operating leverage and cash flows, which are closely related to *RShare* but less related to switching options in my model.

To check the robustness of the results that *RShare* predicts firm risk through the switching options channel, I examine changes in firms' switching options and systematic risk after recessions. My model suggests that after a significant negative aggregate shock, high-*RShare* firms exercise more of their switching options, making them similar to low-*RShare* firms in terms of both their production structures and their systematic risk. I confirm this prediction by showing that in the three years after the beginning of the 2001 and 2008-09 recessions, firms with high and low *RShare* prior to the recessions become more similar in terms of both machine-to-employment ratio and operating leverage. In addition, the difference between their market betas is no longer significant. These results support the view that high-*RShare* firms have lower exposure to systematic risk because they have more switching options.

Finally, I examine additional predictions of the model to provide supporting evidence on the substitutability of routine-task labor by machines. Comparative statics in my model suggests that a negative shock to machine prices will make firms more willing to replace their routine-task labor with machines. I explore an unanticipated law introduced in October 2001, namely, the Job Creation and Worker Assistance (JCWA) Act of 2002, which offers a 30% temporary tax bonus on corporate investment in equipment. Using the Act as an equivalent negative shock to machine prices, I conduct a simple counterfactual experiment by asking what would have happened to the employment of high-routine occupations if the JCWA Act

⁸Sorting based on *RShare* across all firms, instead of within industry, generates more than -4.8% return spread per year. See the Internet Appendix for more details.

had not been introduced. Consistent with my model’s prediction, I find the JCWA Act led to a 0.3 million job loss in high-routine occupations from October 2001 to October 2002 but no effect on low-routine occupations.

This paper adds to existing literature by introducing a new channel through which investment opportunities impact asset prices. The majority of studies in this area regard investment opportunities as growth options (see Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), Liu, Whited, and Zhang (2009), and Ai and Kiku (2013), among others). To the best of my knowledge, this paper is the first to study the asset pricing implications of a firm’s switching options to reduce production costs through labor-technology substitution. By separating growth options (to increase output) and switching options (to increase efficiency) in my model, I show that while growth options increase firms’ exposure to systematic risk, switching options lower that exposure. Thus, my model complements existing theories and improves our understanding of the links between firms’ investment opportunities and stock returns.

My empirical findings contribute to a growing literature on labor heterogeneity and the cross-section of stock returns.⁹ Eisfeldt and Papanikolaou (2013) show that firms with a high level of organization capital are more exposed to priced technology frontier shocks, since key talent that owns a firm’s organization capital can walk away in response to these shocks. Donangelo (2014) shows that firms in industries with mobile workers are more exposed to aggregate shocks, since mobile workers can walk away for outside options in bad times, making it difficult for capital owners to shift risk to workers. My work differs from these studies by exploring a new aspect of labor heterogeneity, namely, the heterogeneous ability of a firm to replace its workers with machines. Hence, this paper derives the effect of labor heterogeneity on firm risk through the channel of investment opportunities, while most previous studies derive this effect through operating leverage.

This paper is also related to recent studies on embodied technology and the cross-section of stock returns.¹⁰ Kogan and Papanikolaou (2014) show that shocks to technologies embodied

⁹A partial list of papers in this literature is Gourio (2007), Chen, Kacperczyk, and Ortiz-Molina (2011), Eisfeldt and Papanikolaou (2013), Kuehn, Simutin, and Wang (2013), Belo, Lin, and Bazdresch (2014), Donangelo (2014), Belo, Lin, Li, and Zhao (2015), Donangelo, Gourio, and Palacios (2015), and Tuzel and Zhang (2015), among others.

¹⁰A partial list of papers in this literature is Papanikolaou (2011), Garleanu, Panageas, and Yu (2012), Garlappi and Song (2013), Kogan and Papanikolaou (2013), and Kogan and Papanikolaou (2014), among others.

in new capital equipment affect the cross-section of stock returns. My paper does not address shocks to labor-saving technology that is embodied in machines. Rather, I show that a firm's decision to adopt labor-saving technology is related to the business cycle. Hence, while previous studies tend to assume embodied technological shocks as a second risk factor, my model maintains a single risk factor that is based on aggregate shocks.

This paper builds on the macroeconomics and labor economics literature. Specifically, my model setup is based on earlier studies that analyzes heterogeneous labor and capital inputs in production functions. [Stokey \(1996\)](#) considers a three-factor production function that treats skilled labor, unskilled labor, and physical capital as separate production factors and assumes physical capital as a substitute for unskilled labor. [Krusell, Ohanian, Rios-Rull, and Violante \(2000\)](#) extend this framework by further dividing physical capital into structure and equipment and emphasizing that only technologies that affect the stock of equipment can impact the wage spread between skilled and unskilled labor. More recently, [Autor, Levy, and Murnane \(2003\)](#) explicitly model routine-task labor and computers as substitutable production factors and show that the decline in routine-task jobs is associated with the increased use of computers. In this paper, instead of modeling a firm's production function, I model firms as having two types of projects. While both types of projects require some non-routine-task labor, they differ in that unautomated projects require routine-task labor while automated projects require machines.

My empirical measure of routine-task labor is based on recent labor economics literature on skill-biased technological change. Starting with the seminal work of [Autor, Levy, and Murnane \(2003\)](#), who provide a novel measure of routine-task labor to proxy for jobs that can be substituted by computerization, an emerging literature analyzes and improves this measure.¹¹ I improve the latest version of this measure that is used by [Autor and Dorn \(2013\)](#) to account for changes in technology over time. Applying the measure to detailed establishment-level data, this paper is the first to measure firm-level share of routine-task labor. While most studies focus on the secular trend of routine-task labor being replaced by computerization, my work is the first to analyze firms' decision on labor-technology substitution over the business cycle and its implications for stock returns.¹²

¹¹[Acemoglu and Autor \(2011\)](#) provide a comprehensive review of this literature.

¹²[Jaimovich and Siu \(2014\)](#) study how routine-task labor contributes to the connection of job polarization and jobless recovery over the business cycle, but do not explore the substitutability of routine-task labor by technology.

The rest of this paper is organized as follows. Section I develops the theoretical model. Section II details my procedure for measuring firms' share of routine-task labor. Section III presents the empirical tests of the model's predictions. Section IV concludes.

I. The Model

There are a large number of infinitely lived firms that produce a homogeneous final good. Firms behave competitively, and there is no explicit entry or exit. Firms are all-equity financed, hence firm value is equal to the market value of its equity.

A. Technology

A.1. Projects

Each firm owns a finite number of individual projects. Firms create projects over time through investment, and projects expire randomly.¹³ The cash flows generated by project j of firm i at time t are given by

$$A_{i,j,t} = e^{x_t + z_{i,t} + \epsilon_{j,t}}, \quad (1)$$

where x_t is the aggregate shock that affects the cash flows of all existing projects, and $z_{i,t}$ and $\epsilon_{j,t}$ are the firm-specific shock and the project-specific shock, respectively. While aggregate uncertainty contributes to the aggregate risk premium, the firm- and project-specific shocks contributes to firm heterogeneity in the model. Similar to Gomes, Kogan, and Zhang (2003), I assume that shocks evolve according to mean-reverting processes to capture their path-dependency property. Different from Gomes, Kogan, and Zhang (2003), I assume that the rate of mean-reversion are the same for all levels of shocks for tractability. Specifically,

$$\begin{aligned} dx_t &= -\theta x_t dt + \sigma_x dB_{xt} \\ dz_{i,t} &= -\theta z_{i,t} dt + \sigma_z dB_{zt} \\ d\epsilon_{j,t} &= -\theta \epsilon_{j,t} dt + \sigma_\epsilon dB_{\epsilon t}, \end{aligned} \quad (2)$$

¹³Firms with no existing projects can be viewed as firms waiting to enter the product market. In this sense, my model endogenously takes into account the entry and exit of firms.

where $\theta \in (0, 1)$ is the rate of mean-reversion and B_{xt} , B_{zt} , and $B_{\epsilon t}$ are Wiener processes independent of each other. Hence, the dynamics of $a_{i,j,t} = \log(A_{i,j,t})$ evolve according to

$$da_{i,j,t} = -\theta a_{i,j,t} dt + \sigma_a dB_t, \quad (3)$$

where $\sigma_a = \sqrt{\sigma_x^2 + \sigma_z^2 + \sigma_\epsilon^2}$ and $B_t = (\sigma_x B_{xt} + \sigma_z B_{zt} + \sigma_\epsilon B_{\epsilon t})/\sigma_a$, which is also a Wiener process. In the following analysis, I suppress the firm index i and project index j for notational simplicity unless otherwise indicated.

A project is characterized as follows. First, each project requires an initial investment of I at the project's initiation date. Second, each project requires fixed units of non-routine-task labor such as managers to perform the non-routine tasks, which demands a total wage of c_N per unit of time. Finally, each project also requires factor input to perform routine tasks, and the project generates cash flows when both non-routine tasks and routine tasks are performed.

A project's routine tasks can be performed by either fixed units of routine-task labor or fixed units of machines. If the firm hires routine-task labor, it pays a total wage of c_R per unit of time, and the project starts producing immediately. Production incurs a fixed cost of f per unit of time. I refer to projects using routine-task labor as *unautomated projects*. If the firm invests in machines, the firm pays I_M at the initiation date, but it takes the firm T units of time to adapt the technology embodied in the machines for its project, during which time the project does not generate any cash flows.¹⁴ After the first T periods, the project starts generating cash flows and incurs a fixed cost of f per unit of time. Using machines does not incur additional fixed costs.¹⁵ I refer to projects using machines as *automated projects*. All capital, once purchased, has zero resale value.

Given the above setup, the operating profits for an unautomated project are

$$\pi_U(t) = A_t - c_R - c_N - f, \quad (4)$$

¹⁴I assume that projects have heterogeneous needs for technology. Hence, each project requires some time to customize the technology for its own needs.

¹⁵Alternatively, we can allow for a fixed cost of using machines, but regard the cost as part of f . In this case, c_R is the excess cost of using routine-task labor to using machines.

and the operating profits for an automated project initiated at time t_0 are

$$\pi_A(t_0; t) = \begin{cases} -c_N & t \leq t_0 + T \text{ (technology-adoption periods)} \\ A_t - c_N - f & t > t_0 + T \text{ (production periods)}. \end{cases} \quad (5)$$

A.2. Firm Dynamics

Given that each project uses a fixed amount of input factors, changes in a firm's capital and labor in the model are represented by changes in the *number* of the firm's unautomated and automated projects. Such changes are assumed to arise for one of three reasons. First, at any point of time, projects can expire independently at a rate of δ . Second, following [Kogan and Papanikolaou \(2014\)](#), a new project can exogenously become available to the firm according to a Poisson process with an arrival rate of λ . At the time of arrival, the project-specific shock of the new project is at its long-run average value, that is $\epsilon_t = 0$. Such investment opportunities cannot be postponed or preserved. If the firm decides to undertake the new project, it can choose to initiate either an unautomated or an automated project.

Third, a firm can endogenously switch its existing projects' type at any time. If the firm decides to switch a project from unautomated to automated, it lays off the project's routine-task labor and invests I_M in machines. I assume that technology has evolved to a stage such that automating unautomated projects is profitable. That is, I assume that I_M is significantly lower than the present value of all future wages paid to routine-task labor, $I_M \ll \frac{c_R}{r+\delta}$.¹⁶ For simplicity, I assume that the process of the project-specific shock is not affected after a project's type is switched. Given that machines have zero resale value and routine-task labor is significantly more costly than machines, switching from automated projects to unautomated projects is never optimal.¹⁷

A firm's existing projects are the sum of its unautomated projects and its automated

¹⁶The literature on investment-specific technological shocks argues that a large part of the technological progress after World War II took place in equipment and software and can be inferred from the decline in the quality-adjusted price of new capital goods. See [Greenwood, Hercowitz, and Krusell \(1997\)](#), [Papanikolaou \(2011\)](#), and [Kogan and Papanikolaou \(2014\)](#) for more details.

¹⁷I do not allow the firm to switch an automated project to a new automated project to ensure that the general assumption applies to both unautomated and automated projects that the firm cannot endogenously suspend production for purposes other than adopting labor-saving technology. Technically, I assume that if the firm switches an automated project to a new automated project, the firm does not need to take another T periods to learn the technology for the project, and the project starts incurring production costs immediately. Under this assumption, such choice is never optimal.

projects. Suppose at time t that a firm has $n_{U,t}$ unautomated projects and $n_{A,t}$ automated projects. Then, the firm's share of routine-task labor ($RShare$) is defined as the ratio of the total wages paid to its routine-task labor relative to its total wage expense:

$$RShare(t) = \frac{c_R n_{U,t}}{c_N(n_{U,t} + n_{A,t})}. \quad (6)$$

B. Valuation

Following Berk, Green, and Naik (1999) and Zhang (2005), I specify the stochastic discount factor explicitly as

$$\frac{d\Lambda_t}{\Lambda_t} = -r dt - \sigma_\Lambda dB_{xt}, \quad (7)$$

where r is the interest rate and σ_Λ is the price of risk.

B.1. The Value of Automated Projects

Since automated projects do not have any options, their value is simply the discounted value of their future profits. For an automated project initiated at t_0 ,

$$\begin{aligned} V_A(t_0; t) &= E_t \int_0^\infty e^{-\delta s} \frac{\Lambda_{t+s}}{\Lambda_t} \pi_A(t_0, t+s) ds \\ &= \int_{t'}^\infty A_t^{e^{-\theta s}} e^{g(s)} ds - \frac{c_N + e^{-(r+\delta)t'} f}{r + \delta}, \end{aligned} \quad (8)$$

where $t' = \max(t_0 + T - t, 0)$ is the time to wait (for the project to generate cash flows) and $g(s) = (-\delta - r)s - \frac{\sigma_x \sigma_\Lambda}{\theta} (1 - e^{-\theta s}) + \frac{\sigma_a^2}{4\theta} (1 - e^{-2\theta s})$. Appendix A.1 provides the derivation.

B.2. The Value of Unautomated Projects

The value of an unautomated project can be divided into the value of assets in place, $V_U^{AP}(t)$, and the value of switching options, $V_U^{SO}(t)$:

$$V_U(t) = V_U^{AP}(t) + V_U^{SO}(t). \quad (9)$$

The value of assets in place is simply the discounted value of future profits:

$$\begin{aligned} V_U^{AP}(t) &= E_t \int_0^\infty e^{-\delta s} \frac{\Lambda_{t+s}}{\Lambda_t} \pi_U(t+s) ds \\ &= \int_0^\infty A_t e^{-\theta s} e^{g(s)} ds - \frac{c_R + c_N + f}{r + \delta}. \end{aligned} \quad (10)$$

The value of the switching option can be calculated as the discounted value of the optimal payoff:

$$V_U^{SO}(t) = \text{Payoff}(t + \tau) \hat{\mathbb{E}}_t[e^{-(r+\delta)\tau}], \quad (11)$$

where τ is the optimal stopping time for the firm to switch technology and $\hat{\mathbb{E}}_t[\cdot]$ is an expectation operator under the risk-neutral probability measure. The payoff function is

$$\begin{aligned} \text{Payoff}(t) &= V_A(t; t) - V_U^{AP}(t) - I_M \\ &= \frac{c_R + f[1 - e^{-(r+\delta)T}]}{r + \delta} - I_M - \int_0^T A_t e^{-\theta s} e^{g(s)} ds \\ &= P(A_t). \end{aligned} \quad (12)$$

Hence, the switching option can be viewed as an investment opportunity with a fixed benefit, a fixed direct cost, but a variable opportunity cost that is low if the project is doing poorly. Following Dixit and Pindyck (1994), I prove the following in Appendix A.2.

Proposition 1 (Optimal exercise of switching options): *A firm optimally switches a project from unautomated to automated when the project's cash flows, A_t , are below a threshold A^* , where A^* satisfies*

$$\frac{d[P(A^*)O(A_t, A^*)]}{dA^*} = 0 \quad \forall A_t \geq A^*, \quad (13)$$

where $O(A_t, A^*) = \hat{\mathbb{E}}_t[e^{-(r+\delta)\tau}]$ is the optimal discounting of the option payoff.

The analytical expression of $O(A_t, A^*)$ is provided in Appendix A.2.

Corollary 1 (Cross-section of investment for technology switching): *Keeping all else equal, a firm with a high $RShare$ invests more in machines than a firm with a low $RShare$ if the economy experiences a negative shock, that is, $dx_t < 0$.¹⁸*

¹⁸“Keeping all else equal” in this corollary means that we are comparing two firms with the same number of projects and the same set of cash flows for their projects. The only difference is that the high- $RShare$ firm has more unautomated projects than the other firm.

Proof: This follows directly from Proposition 1.

Corollary 2 (Cross-section of routine-task employment under negative aggregate shocks): *Keeping all else equal, a firm with a high RShare reduces more of their routine-task labor than a firm with a low RShare if the economy experiences a negative shock, that is, $dx_t < 0$.*

Proof: This follows directly from Proposition 1.

Finally, the value of the unautomated project is

$$V_U(t) = \int_0^\infty A_t e^{-\theta s} e^{g(s)} ds - \frac{c_R + c_N + f}{r + \delta} + P(A^*)O(A_t, A^*). \quad (14)$$

B.3. The Value of Growth Opportunities

Given that the investment opportunities cannot be postponed, firms optimally decide to undertake new projects based on the NPV rule. The optimal exercise of the growth options is thus characterized by comparing the incremental value of undertaking a new unautomated project, $V_U(t + s) - I$, undertaking a new automated project, $V_A(t + s; t + s) - I_M - I$, and not undertaking a project.

The optimal exercise of switching options indicates that firms prefer undertaking new automated projects over undertaking new unautomated projects if $A_t < A^*$.¹⁹ Let A^{**} be the threshold for firms to undertake a new project. A^{**} is determined by making the investment in the new project a zero NPV project, that is, A^{**} is the solution to

$$V_A(t; t) - I_M - I = 0 \quad (15)$$

or the solution to

$$V_U(t) - I = 0. \quad (16)$$

I summarize these results in the following proposition.

Proposition 2 (Optimal exercise of growth options): *A firm optimally undertakes a new project when the cash flows of the new project, $A_t = e^{x_t + z_t + 0}$, are above a threshold A^{**} . A^{**} is the minimum of the solutions to equations (15) and (16).*

¹⁹To see this, suppose that a firm undertakes a new unautomated project when $A_t < A^*$. Then, by Proposition 1, the firm will immediately switch the project to automated.

If $A^{**} < A^*$, firms undertake an automated project when $A^{**} < A_t \leq A^*$ and undertake an unautomated project when $A_t > A^*$.

If $A^{**} \geq A^*$, firms undertake an unautomated project when $A_t > A^{**}$.

Corollary 3 (Procyclical aggregate investment): *All firms are more likely to invest in new projects if the economy experiences a positive shock, that is, $dx_t > 0$.*

Proof: This follows directly from Proposition 2.

This corollary helps to generate procyclical aggregate investment in the model.

Corollary 4 (Cross-section of investment for growth): *If $A^{**} < A^*$, conditional on undertaking new projects, firms with high idiosyncratic shocks, z_t , are more likely to undertake new unautomated projects, and firms with low idiosyncratic shocks are more likely to undertake new automated projects.*

Proof: This follows directly from Proposition 2.

The intuition of this corollary is straightforward. Because new unautomated projects can start generating cash flows more quickly than new automated projects, they are preferable to be undertaken for expansions when firms are doing well.²⁰ This corollary has two implications in the model. First, it helps generate a stationary distribution of the two types of projects, since in equilibrium, while existing unautomated projects are switched to automated ones, new unautomated projects are also undertaken.

Second, this corollary also generates predictions in the cross-section of machinery investment in good times. Because high-*RShare* firms, on average, are more likely to have high firm-specific shocks, they are more likely to hire routine-task labor instead of investing in machines during good times than low-*RShare* firms.

Corollary 5 (Cross-section of routine-task employment under positive aggregate shocks): *If $A^{**} < A^*$, keeping all else equal, a firm with a high *RShare* and a high firm-level shock is more likely to hire routine-task labor than a firm with a low *RShare* and a low firm-level shock if the economy experiences a positive shock, that is, $dx > 0$.*

²⁰This argument is consistent with Berger (2012), who argues that firms grow “fat” during booms and streamline their production during recessions.

Given that the project-specific shock of any new project is at its long-term mean, the present value of growth opportunities is a function of the aggregate shock and the firm-specific shock:

$$\begin{aligned} PVGO(t) &= E_t \int_{s=0}^{\infty} \lambda \frac{\Lambda_{t+s}}{\Lambda_t} \max [V_U(t+s) - I, V_A(t+s; t+s) - I_M - I, 0] ds \\ &= G(x_t, z_t). \end{aligned} \tag{17}$$

B.4. Firm Value

At any time t , a firm may have $n_{U,t}$ unautomated projects and $n_{A,t}$ automated projects that the firm previously undertook. Let $V_{U,l}(t)$ denote the value of the l th unautomated project that the firm undertook, where $l = 1, 2, \dots, n_{U,t}$. Let $t_k \leq t$ denote the time when the k th automated project was undertaken, and $V_{A,k}(t_k; t)$ the value of the k th automated project, where $k = 1, 2, \dots, n_{A,t}$. Firm value equals the value of all existing projects plus the present value of growth opportunities:

$$V(t) = \sum_{l=1}^{n_{U,t}} V_{U,l}(t) + \sum_{k=1}^{n_{A,t}} V_{A,k}(t_k; t) + PVGO(t) \tag{18}$$

C. Firm Risk

The equity beta of a project or a firm is defined as the scaled covariance of its value and the stochastic discount factor,

$$\beta = - \frac{\text{Cov} \left(\frac{dV}{V} \frac{d\Lambda}{\Lambda} \right)}{\text{Var} \left(\frac{d\Lambda}{\Lambda} \right)}. \tag{19}$$

From equation (18), we know that a firm's beta is the weighted average of the betas of its existing projects and the beta of its growth opportunities,

$$\beta_f = \sum_{l=1}^{n_U} \frac{V_{U,l}}{V} \beta_{U,l} + \sum_{k=1}^{n_A} \frac{V_{A,k}}{V} \beta_{A,k} + \frac{PVGO}{V} \beta_{PVGO}. \tag{20}$$

To understand the connection between a firm's *RShare* and its beta, I examine the riskiness of the two types of projects.

I first compare betas of an unautomated project and an automated project with the same set of shocks $\{x_t, z_t, \epsilon_t\}$. The assets in place component of the unautomated project is riskier

than the automated project due to the higher operating leverage induced by the fixed cost paid to routine-task labor. The switching option, which has a negative beta, lowers the beta of the unautomated project, making comparison of the two types of projects difficult.

From equation (12), we see that when the project's cash flows A_t approach A^* , the value of the unautomated project approaches the value of a newly initiated automated project minus the cost of investment in machines I_M , that is,

$$\lim_{A_t \rightarrow A^*+} V_U(t) = V_A(t; t) - I_M. \quad (21)$$

Under mild parameter restrictions provided in Appendix A.3, a newly initiated automated project is likely to be less risky than a goods-producing automated project for a given set of shocks, because skipping T periods of production makes the project value less sensitive to aggregate shocks. In this case, an unautomated project is less risky than an automated project with the same set of shocks.

When the project's cash flows A_t approach infinity, the switching option is far out of the money and the value of an unautomated project approaches the value of its asset in place, that is,

$$\lim_{A_t \rightarrow \infty} V_U(t) = V_U^{AP}(t). \quad (22)$$

Given that the assets in place of the unautomated project is riskier than the goods-producing automated project, the unautomated project is riskier if A_t approaches infinity. Putting these results together, I prove the following in Appendix A.3:

Proposition 3 (Comparison of project risks): *If the condition in Appendix A.3 holds, there exists a threshold of cash flows $\bar{A}(t_0) \in (A^*, +\infty)$ such that an automated project initiated at time t_0 is riskier than an unautomated project with the same set of shocks $\{x_t, z_t, \epsilon_t\}$ when $A_t < \bar{A}(t_0)$.*

The equation that determines $\bar{A}(t_0)$ is provided in Appendix A.3.

D. Simulation Results

Given that the risk comparison between automated and unautomated projects holds conditionally in Proposition 3, I simulate the model under economically reasonable parameters to examine whether the switching option channel is powerful enough to generate lower risk

premia for high-*RShare* firms in the cross-section. In addition, this test also helps to examine whether the predictability of *RShare* on stock returns is robust to the dynamic setting in which *RShare* evolves endogenously.

Panel A of Table 1 summarizes the parameter choices. My model setup shares many similar features with Kogan and Papanikolaou (2014), who also develop a model at the project level. Hence, I adopt the parameter values used by Kogan and Papanikolaou (2014) as many as possible. Specifically, I adopt the parameter values in Kogan and Papanikolaou (2014) for volatilities of x_t , z_t and ϵ_t , rate of mean-reversion, risk-free rate, and project obsolescence rate.²¹ The required time for technology adoption is absent in the model of Kogan and Papanikolaou (2014). I thus set the required time to be three quarters following the time-to-build literature (e.g., Kydland and Prescott (1982) find that a reasonable range for the average construction period is three to five quarters).

Given that Kogan and Papanikolaou (2014) have two factors in their pricing kernel while my model only has one, I choose the price of risk to match the equal-weighted aggregate risk premium. Because I assume a constant price of risk in my stochastic discount factor for tractability, I need an unrealistically high value for the price of risk to match the risk premium.²² In addition, my model has a much simpler setting for growth opportunities compared to the model of Kogan and Papanikolaou (2014), I thus set the project arrival rate to match the aggregate dividend growth rate.

The literature offers less guidance on the cost of different production factors at the project level. I thus match several moments to pin down these parameters. The per-project cost for using routine-task labor, c_R , and non-routine-task labor, c_N , are chosen to match the aggregate share of routine-task labor in my sample. The rest of the operating cost, f , is chosen to match the correlation between gross hiring and GDP growth. Cost of project initiation, I , and cost of machines per automated project, I_M , are chosen to match the correlation between gross investment and GDP growth. See Panel B of Table 1 for the moments.

Plugging these parameter values into equations (13), (15), and (16), we obtain the optimal

²¹Kogan and Papanikolaou (2014) use 0, 0.35, and 0.5 as the rates of mean-reversion for the aggregate shocks, firm-level shocks, and project-level shocks, respectively. My model requires the rate of mean-reversion to be the same for all levels of shocks. Thus, I choose the rate of mean-reversion to be 0.35 in my simulation.

²²It is well-known in the literature that a countercyclical price of risk in the stochastic discount factor is crucial for generating high risk premium. See alternative specifications of stochastic discount factor in Zhang (2005) and Jones and Tuzel (2013).

thresholds for exercising switching options and growth options. Under these parameter values, $A^* = 0.75$ and $A^{**} = 0.81$, while the 40th, 50th, and 60th percentiles of A_t are 0.63, 1.00, and 1.58, respectively.

[TABLE 1 HERE]

Using the above parameter choices, I simulate the model at monthly frequency ($dt = 1/12$) for 1,000 firms over 1,200 periods. I drop the first 600 periods to eliminate dependence on initial values. I simulate 100 times and calculate the standard errors across simulations. I describe my procedure for model discretization and simulation in Appendix B.

Table 2 reports portfolio sorting of stock returns by firms' share of routine task labor ($RShare$) using model simulated data. The excess returns monotonically decrease from 14.20% to 11.96% per year from the lowest $RShare$ quintile to the highest $RShare$ quintile. Comparing the highest and the lowest $RShare$ quintile portfolios yields a -2.24% return spread per year, which is somewhat smaller than what I find in the data, -3.10% . One reason could be that the simulation under the parameter values cannot generate enough cross-sectional dispersion in terms of $RShare$. The $RShare$ of the five portfolios ranges from 0.06 to 0.22 in the model, but from 0.02 to 0.39 in the data. The market beta shows a similar monotonically decreasing pattern and has a spread of -0.18 for the long-short portfolio. In summary, these results suggest that switching options serve as an economically significant channel that dominates countering forces such as the operating leverage channel and leads to lower risk premium for high- $RShare$ firms in the model.

[TABLE 2 HERE]

II. Measuring a Firm's Routine-Task Labor

A. Data and Methodology

My model suggests that a firm's $RShare$ can be measured as the ratio of the total wages paid to its routine-task labor relative to its total wage expense (see equation (6)). In this section, I describe the data and methodology that I use to construct firms' $RShare$.

I construct $RShare$ as follows. First, I decompose each firm's labor cost by its employees'

occupations. Second, I identify the occupations in each year that can be regarded as routine-task labor. With these two steps complete, I construct firms' *RShare* following the definition in equation (6).

To obtain firms' occupational composition, I use microdata at the establishment-occupation level provided by the OES program of the Bureau of Labor Statistics (BLS). This dataset covers surveys that track employment by occupations in approximately 200,000 establishments every six months over three-year cycles from 1988 to 2014. These data represent on average 62% of the non-farm employment in the U.S. The data use the OES taxonomy occupational classification with 828 detailed occupation definitions before 1999, and the Standard Occupational Classification (SOC) with 896 detailed occupation definitions thereafter. Beyond occupational information, the microdata also cover establishments' location and industry affiliation, as well as their parent company's employer identification number (EIN), legal name, and trade name.

The OES microdata include estimates of the median hourly wage for each occupation in each establishment from 1997 onwards. For years before 1997, I estimate the hourly wage from the Census Current Population Survey Merged Outgoing Rotation Groups (CPS-MORG) obtained from the website of National Bureau of Economic Research. From the CPS-MORG, I calculate the hourly wage for 504 occupations in 13 broad industries.²³ When possible, I impute the hourly wage for each occupation-industry in the OES microdata. Otherwise, I use either the estimated nationwide hourly wage for the OES occupation or the industry-level hourly wage for the major group of the OES occupation. The total wages paid to an occupation in an establishment is simply the product of the employment and the hourly wage.

I aggregate establishments to Compustat firms using EINs and supplement the matching by using legal names.²⁴ The OES program started keeping the parent firm's EIN for estab-

²³CPS-MORG uses the Census Occupation Codes (COC) to classify its occupations and the Census Industry Codes (CIC) to classify its industries. I calculate the average hourly wage of individuals aged 18 to 65 within each COC and broad CIC group, weighted by the personal earnings weights. I build a crosswalk between COC and OES occupational classifications by first linking both codes to a much more detailed occupational classification from the Dictionary of Occupational Titles and then assigning a COC occupation to an OES occupation if the COC occupation overlaps with more than 50% the OES occupation's detailed occupation. Similarly, I crosswalk COC to the major groups of OES occupations. I also crosswalk CIC broad industry groups to 3-digit Standard Industry Classifications, which is the industry classification used in the OES microdata.

²⁴Some states allow establishments that use professional payroll firms to report the payroll firms' EINs instead of the establishment owners' EINs. I hand-collect the legal names and EINs of professional payroll

lishments after 1999. For the sample between 1990 and 1999, I backout the EIN information by linking the OES establishments through the BLS’s internal identifiers to the Quarterly Census of Employment and Wages (QCEW) database, which has the EIN for the universe of establishments over the 1990 to 2014 period. For the OES sample in 1988 and 1989, I match the establishments to Compstat firms using legal names as no EINs are available. A firm’s labor composition at year t is captured by the occupation composition for all employees the firm hires in its establishments in years $t - 2$, $t - 1$, and t .²⁵ This procedure identifies the occupation composition in terms of labor cost for an average of 3857 Compustat firms in each year from 1990 to 2014.

I next identify routine-task labor in the economy so that I can calculate firms’ $RShare$. My methodology is based on a procedure commonly used in the labor economic literature and is closest to Autor and Dorn (2013). Specifically, I use the revised fourth [1991] edition of the U.S. Department of Labor’s Dictionary of Occupational Titles (DOT) to obtain descriptions of occupations classified at a very detailed level. For each DOT occupation, I select the occupation’s required skill level in performing five categories of tasks: *abstract analytic*, *abstract interactive*, *routine cognitive*, *routine manual* and *non-routine manual* tasks.²⁶ I re-scale these skill levels to values between 1 and 10. I then take the average of the abstract analytic and abstract interactive skill levels as the skill level required by the occupation in performing abstract tasks. Similarly, I take the average of the routine cognitive and routine manual skill levels as the skill level required by the occupation in performing routine tasks. Given that the revised edition of the DOT is available after 1991, to avoid using future information, I employ a similar procedure using data from the fourth [1977] edition of the DOT to create measures of the required skill level in performing abstract, routine, and non-

firms and exclude establishments with legal names or EINs that match the payroll firms. Another concern is that some firms may have multiple EINs, especially for large firms that operate in multiple states. Failure to identify all EINs with common ownership would lead to measurement error in $RShare$ and increase the standard errors in my analysis. Supplementing the matching using legal names improves the number of matches marginally, since the names are subject to typing errors and missing information. In unreported analysis, I conduct a fuzzy matching via legal names using stata ado file “relink” written by Michael Blasnik. The resulting measure is very close to the $RShare$ measure.

²⁵I include the establishments from the past two years because the OES survey covers each establishment in 3-years cycles. This methodology provides better coverage of a firm’s operation than using only firms’ establishments at year t .

²⁶Specifically, abstract analytic skill is measured by mathematical skill. Abstract interactive skill is measured by direction, control, and planning skills. Routine cognitive skill is measured by skills in setting limits, tolerances, or standards. Routine manual skill is measured by finger dexterity. Non-routine manual skill is measured by eye-hand-foot coordination skill.

routine manual tasks for occupations before 1991.

I crosswalk the 1977 DOT occupations to the OES occupations for the 1988 to 1990 period and crosswalk the 1991 DOT occupations to the OES occupations for the 1991 to 2014 period. The task skill measures for the OES occupations are the average of the skill measures for the corresponding DOT occupations following a weighting approach proposed by Autor, Levy, and Murnane (2003).²⁷

Following Autor and Dorn (2013) and Autor, Dorn, and Hanson (2013), I define the routine-task intensity (RTI) score for each OES occupation as

$$RTI_k = \ln(T_k^{\text{Routine}}) - \ln(T_k^{\text{Abstract}}) - \ln(T_k^{\text{Manual}}), \quad (23)$$

where T_k^{Routine} , T_k^{Abstract} , and T_k^{Manual} are the routine, abstract, and non-routine manual task skill levels required by occupation k , respectively.

Routine-task labor is defined as follows. In each year, I select all workers in the OES sample in the current year as well as the previous two years to represent the current year's labor force. I then sort all workers in the selected sample by their occupations' RTI scores. I define workers as routine-task labor if their RTI scores fall in the top quintile of the distribution for that year.²⁸

I construct $RShare$, the share of routine-task labor, for each firm in year t as

$$RShare_{j,t} = \sum_k \mathbb{1} [RTI_k > RTI_t^{P80}] \times \frac{emp_{j,k,t} \times wage_{j,k,t}}{\sum_k emp_{j,k,t} \times wage_{j,k,t}}, \quad (24)$$

where $\mathbb{1}[\cdot]$ is the index function, RTI_k is the RTI score of occupation k , RTI_t^{P80} is the 80 percentile of RTI scores for the labor force at time t , and $emp_{j,k,t}$ and $wage_{j,k,t}$ are the number of employees and the hourly wages of occupation k in firm j at time t , respectively.

²⁷The DOT occupational classification is much finer than the OES taxonomy classification or the SOC. Thus, the crosswalk from DOT to OES occupations is a simple aggregation. Following Autor, Levy, and Murnane (2003), I use the April 1971 CPS sample to obtain the employment weights of the 1977 DOT occupations in the population. DOT occupations that do not appear in the April 1971 CPS sample is assigned with minimal population (i.e. one person) in the employment weights calculation. I use the crosswalk of 1977 DOT to 1991 DOT occupations provided by David Autor to obtain population weights for the 1991 DOT occupations. I aggregate the task skill levels from DOT to OES occupations using the employment weights.

²⁸In the Internet Appendix, I classify routine-task labor at alternative cutoffs, such as the top quartile of the RTI score distribution, and find very similar results in all of the main tests. The OES survey changed design in 1996, making it difficult to represent the total labor force. I thus use the 1995 definition of routine-task labor to proxy for the total labor force in 1996. The definition of routine-task labor for 1997 is based on the sorting of workers in the 1996 and 1997 samples.

I finalize my sample selection by imposing additional requirements based firms' accounting and stock return information. Appendix C provides a detailed description of the sample selection as well as definitions of financial and accounting variables. I end up with 47,684 firm-year observations in 17 industries based on the Fama and French (1997) classification.

B. Validation

B.1. Characteristics of Routine-Task Labor

To evaluate my measure of routine-task labor, I examine the characteristics of occupations identified as routine-task labor. Panel A of Table 3 shows that while routine-task labor accounts for a large portion of the clerical, production, and sales occupations, which is consistent with previous studies (e.g., Jaimovich and Siu (2014)), it also accounts for a significant portion of the service, professional, and agriculture occupations.

Routine-task labor can potentially be misinterpreted as occupations that can be outsourced to foreign countries such as China and India. If they are indeed the same, routine-task labor should primarily capture the occupation's substitutability by remote but low-cost labor instead of substitutability by machines. Blinder (2009) and Blinder and Krueger (2013) argue that essentially any job that does not need to be done in person can ultimately be outsourced, regardless of whether it is routine or non-routine. Using the offshorability measure of occupations created by Acemoglu and Autor (2011), I find supporting evidence. In particular, Panel B of Table 3 shows that offshorability has a small negative correlation with both the routine-task labor dummy and the RTI score, indicating that these measures capture different aspects of an occupation.

Many economists argue that jobs susceptible to technological substitution tend to be those of middle-class workers with moderate skills. Consistent with this argument, I find a moderate negative correlation of the routine measures and occupations' median wages and skills. When I further examine whether routine-task workers are more likely to be covered by labor unions, I find no significant correlation between these two attributes, suggesting that unions are unlikely to be a major factor in hiring routine- versus non-routine-task labor.²⁹

²⁹I obtain the union coverage rate for occupations from www.unionstats.com. This union coverage rate is compiled by Barry Hirsch and David Macpherson from the Current Population Survey and updated annually. See Hirsch and MacPherson (2003) for a description of the database. The union coverage rate is given at the COC classification. I crosswalk COC to SOC classification to obtain the union coverage rate for the OES sample in 1999-2014.

In summary, the above results suggest that my measure of routine-task labor is consistent with the characteristics of jobs that can be substituted by machines.

[TABLE 3 HERE]

B.2. Employment over the Business Cycle

I examine routine-task labor by providing graphic evidence on the dynamics of routine-task labor's employment over the business cycle. Such evidence is helpful for understanding firms' decisions on hiring routine-task labor in different economic states, and for linking firms' *RShare* and their exposure to systematic risk. While my measure of routine-task labor, constructed based on the OES data, can be used to capture the time-series impact of technological evolution in replacing labor, it is not suitable for time-series analysis that requires tracking a given set of occupations over time. Moreover, the OES data, based on surveys that cycle each establishment every three years, cannot track changes in routine-task labor at the business cycle frequency.

Conventional methods used in the labor economics literature is not helpful either. A large body of this literature examines the time series of routine-task labor's employment and wages using data from the Census Bureau at the decennial frequency. Such data are not suitable for employment dynamics over the business cycle, which is traditionally defined at the 18- to 96-month frequency. [Jaimovich and Siu \(2014\)](#), who classify routine-task labor based on three major occupation groups, suggest that the CPS monthly sample is helpful for studying the business cycle. I thus adopt a hybrid methodology whereby I define high-routine and low-routine occupations based on the distribution of RTI scores using the 1980 Census data, and examine the business cycle dynamics of the two occupational groups using the CPS monthly basic data.

Following [Autor and Dorn \(2013\)](#), I sort the labor force of the 1980 Census by the RTI score of employees' occupations, constructed using the 1977 DOT. I classify occupations with RTI scores that fall in the top and bottom 30% of the distribution as *high-routine* and *low-routine* occupations, respectively.³⁰ In each month, I aggregate workers in the CPS sample

³⁰The occupations in the top 30% of the 1980 Census distribution closely matches my measure of routine-task labor in 1990, which is defined as the top quintile of the 1990 OES distribution. [Autor and Dorn \(2013\)](#) use the top 33% cutoff to identify routine-task labor.

whose occupations belong to the high-routine or low-routine occupations into two groups, weighted by the sampling weights. I track the employment series of the two groups from January 1989 to December 2013.³¹

Figure 1 plots employment dynamics separately for high-routine occupations and low-routine occupations. Consistent with the literature, we see that the employment of high-routine occupations declines over time, while the employment of low-routine occupations rises. More importantly, the major decreases in the employment of high-routine occupations occur mostly during or shortly after economic recessions. In contrast, the employment of high-routine occupations does not show a significant trend during the expansionary periods. Put together, we see high-routine jobs decline during recessions but do not bounce back during the recovery periods. This supports my model’s prediction that firms replace routine-task labor with machines in bad times.

[FIGURE 1 HERE]

B.3. Wages and Machine Prices over the Business Cycle

I further examine the dynamics of wages and machine prices over the business cycle to investigate possible alternative channels that link routine-task labor and firms’ exposure to systematic risk but are not captured in my model. Specifically, if machine prices drop significantly in bad times, or if routine-task labor is more willing to accept flexible wages than non-routine-task labor, high-*RShare* firms can more easily reduce their labor costs in bad times than low-*RShare* firms. Both channels can consequently lead to the negative relation between firms’ *RShare* and their exposure to systematic risk, although the flexible wage channel cannot explain the lack of recovery of routine-task labor after recessions.

Panel A of Figure 2 plots the quality-adjusted price of equipment from [Israelsen \(2010\)](#) in 1989-2012. This price index is aggregated from the prices of 22 groups of durable equipment and is used in earlier studies as informative about investment-specific technology shocks (see, for example, [Kogan and Papanikolaou \(2014\)](#)). From the plot, we see that the price of ma-

³¹CPS occupation codes changed several times during my sample period. I crosswalk the occupation codes of different years to a unified occupation classification *occ1990*, which is available at the Integrated Public Use Microdata Series maintained by the University of Minnesota. Due to a major change in the CPS occupational classification in 1988, I construct the employment series of high-routine and low-routine occupations starting from January 1989.

chines declines smoothly over time and does not exhibit sizable business cycle properties. In addition, following [Kogan and Papanikolaou \(2014\)](#), I calculate the changes in the detrended log relative real price of equipment to proxy for shocks to machine prices. I find that the correlation between the machine price shocks and the real GDP growth is -25%, indicating that machine prices do not move in the same direction as the aggregate economic states.

Panel B of Figure 2 plots the average hourly wages of high-routine occupations and low routine-occupations from 1989 to 2012 using the sample of the CPS-MORG. The nominal hourly wage for each occupation is the average hourly wage of individuals in that occupation and further aggregated to the high-routine and low-routine group level, weighted by their personal earnings weights. Again, we do not see sizable business cycle properties in the wages of high-routine occupations. In addition, the correlation between the changes in the detrended log real wages for the high-routine and low-routine occupations and real GDP growth are 7% and 18%, respectively. Hence, wages for routine-task labor are not more procyclical than wages for non-routine-task labor.

In summary, the evidence mitigates the concern that my model does not take into account the cyclicity of machine prices and wages.

[FIGURE 2 HERE]

B.4. Evidence from the Job Creation and Worker Assistance Act of 2002

I provide more direct evidence on the substitution of routine-task labor by machines by exploring an unanticipated law introduced in October 2001, namely, the Job Creation and Worker Assistance Act of 2002 (JCWA Act). The JCWA Act offers a 30% tax bonus on new qualified property, mostly machinery and equipment, acquired by companies after September 10, 2001, and placed in to service before September 11, 2004. Comparative statics in my model suggests that shocks that lower machine prices will make firms more willing to replace their routine-task labor with machines. Taking the tax bonus as a shock that lowers the price that firms pay for machines, my model predicts that we should see an extra decline in routine-task labor compared to the case without the shock.³² I conduct a simple counterfactual experiment using the employment series of high-routine occupations

³²[Zwick and Mahon \(2014\)](#) study JCWA Act and firm investment and find that firms respond to the tax bonus by increasing more than 17% of their investments between 2001 and 2004.

constructed in the previous section. Specifically, I ask what would have happened during and after the 2001 recession if the JCWA Act had not been introduced in October 2001.

I match the employment series in the 1990 recession with those in the 2001 recession by pairing July 1990 with March 2001, the starting months of the two recessions. I use the employment series of high-routine occupations and low-routine occupations from October 2000 to October 2002 as the actual data, and use the series from February 1989 to February 1991 as the counterfactual data.³³ I then re-scale the counterfactual series to match the magnitude of the decline in actual employment from the starting month of the 2001 recession (March 2001) to the month in which JCWA Act was introduced (October 2001).

Figure 3 presents the results. Consistent with my model’s prediction, we see that employment of high-routine occupations dropped by an additional 0.9% within one year after the introduction of the JCWA Act, while the counterfactual series increased by 0.2% at the same time. The difference in percentage employment changes between actual and counterfactual series converts to 0.3 million ($1.1\% \times 29$ million) jobs lost in high-routine occupations in the one year after the introduction of JCWA Act. The actual and counterfactual employment series of low-routine occupations, however, do not show much difference.

[FIGURE 3 HERE]

III. Empirical Evidence

The model predicts that in response to unfavorable aggregate shocks, firms with a high share of routine-task labor invest more in machines (Corollary 1) and reduce more of their routine-task labor (Corollary 2) than firms with a low share of routine-task labor, and vice versa if the economy experiences favorable aggregate shocks (Corollary 4 and 5). Due to the hedging channel against unfavorable aggregate shocks, firms with a high share of routine-task labor have lower exposure to systematic risk (Corollary 3). In this section, I empirically test these predictions.

³³The two series are further logged and band-pass filtered to remove fluctuations at frequencies higher than 12 months. See [Christiano and Fitzgerald \(2003\)](#) for details about band-pass filters, and [Jaimovich and Siu \(2014\)](#) for a discussion on the advantages of using a band-pass filter in non-quarterly data.

A. *Routine-Task Labor and Firm Characteristics*

Panel A of Table 4 reports the mean and standard deviation of firms' *RShare* and the number of firm-year observations in each industry sector. The results show that routine-task labor is well-dispersed across industry sectors, with the retail and manufacturing sectors having slightly more routine-task labor, on average. Hence, *RShare* is not likely to be driven by a particular industry. Moreover, the standard deviation of firms' *RShare* is also large in each sector, providing statistical power to my within-industry empirical tests.

I next examine how differences in firms' *RShare* are related to other firm characteristics. To do so, for each year, I sort firms in each Fama-French 17 industry into five portfolios based on their *RShare*. I use within-industry sorting to mitigate the concern that different industries' production technologies may require different intensities of routine-task input relative to non-routine-task input in practice, but my model assumes the intensity to be fixed for all projects.

Panel B of Table 4 shows that high-*RShare* firms have lower ratios of machine to assets and machine to routine-task labor, suggesting that these firms adopt labor-saving technology to a lesser extent than low-*RShare* firms. Consistent with the argument that routine-task labor is more costly to use than machines, I find that high-*RShare* firms have higher operating leverage. In addition, consistent with the model prediction that firms maintain high *RShare* because they have not experienced negative shocks to cash flows, I find that high-*RShare* firms have much higher cash flows than low-*RShare* firms. I also find that high-*RShare* firms have larger size, higher book-to-market, and higher financial leverage.

Finally, I examine whether routine-task labor is a persistent firm characteristic. My model suggests that after exercising their switching options, high-*RShare* firms reduce their *RShare* due to technology switching. To test this prediction, I examine the transition probability of a firm changing from one *RShare* quintile in a year, sorted within industry, to another *RShare* quintile in the next year. Panel C of Table 4 shows that, on average, 24% to 40% of firms opt out of their current quintile portfolio in the next year, implying that *RShare* is a relatively dynamic firm characteristic.

[TABLE 4 HERE]

B. Inspecting the Mechanism

My model suggests that high-*RShare* firms can replace routine-task labor with machines to a greater extent than low-*RShare* firms in response to unfavorable aggregate shocks. To test this prediction, I examine firms' response to aggregate shocks in terms of their investment in machines and their routine-task employment conditioning on their *RShare*.

B.1. Investment in Machines and Aggregate Shocks

Here, I show that high-*RShare* firms invest more in machines than low-*RShare* firms when aggregate shocks are low. Investment in machines is measured by the real annual growth in machinery and equipment at cost (Compustat item FATE) from the property, establishment, and equipment section of a firm's balance sheet. The advantage of using an "at cost" measure is that it does not take into account amortization and depreciation. Hence, any year-over-year change in this variable can be attributed largely to firm investment or divestment. I use the growth in real GDP value added as a proxy for aggregate shocks.³⁴

In the first four columns of Table 5, I run the following panel regression:

$$I_{f,t}^M = b_0 + b_1 RShare_{f,t-1} + b_2 RShare_{f,t-1} \times Shock_t + cX_{f,t-1} + F_f + F_{Ind \times Year} + \epsilon_{ft}, \quad (25)$$

where $I_{f,t}^M$ is firm f 's investment in machines in year t , $RShare_{f,t-1}$ is the firm's *RShare* at the beginning of the year, $Shock_t$ is the aggregate shock in year t , $X_{f,t-1}$ is other firm characteristics that are known to predict investment, including the logarithm of Tobin's Q , market leverage, cash flows, cash holdings, and the logarithm of total assets; and F_f and $F_{Ind \times Year}$ denote firm and industry-year fixed effects, respectively.³⁵

The first two columns of Table 5 report results of regressions without and with controls for firm characteristics using all sample years from 1990 to 2014. I find negative and significant estimates for b_2 , implying that high-*RShare* firms indeed invest more in machines than low-*RShare* firms in bad times.³⁶ In response to a 2% drop in real GDP growth, a firm with

³⁴Alternatively, we could use the aggregate total factor productivity (TFP) series provided by the Federal Reserve Economic Data to proxy for aggregate shocks. The disadvantage of the TFP series is that it is only available up to 2011.

³⁵In the Internet Appendix, I also control for the cross-term of firm characteristics and the aggregate shock for robustness check.

³⁶Using GDP growth as aggregate shocks helps to examine my model predictions on machinery investment in both good times and bad times. To focus on investment in bad times, I conduct a difference-in-differences

RShare one standard deviation higher than its industry peers has machinery investment 0.4% higher.

One caveat is that the Job Creation and Worker Assistance (JCWA) Act introduced at the end of the 2001 recession may have significant impact on the machinery investment in high-*RShare* firms and low-*RShare* firms. If high-*RShare* firms respond to the lowered machinery prices by investing more in machines than low-*RShare* firms, one may be concerned that the results I obtained in the first two columns of Table 5 are not driven by the aggregate shocks but instead by shocks to machine prices. To mitigate this concern, I conduct the test by excluding the years 2002-2004 in Columns (3) and (4), when JCWA Act is active, and find my results remain.

Another concern is that high-*RShare* firms may have less procyclical capital investment than low-*RShare* firms due to factors not observed by economists. To assess this possibility, I conduct a placebo test in which I run the same panel regression but examine investment in other capital rather than machines.³⁷ The last two columns of Table 5 report insignificant results on the cross term. Hence, we do not see that high-*RShare* firms respond to aggregate shocks differently from low-*RShare* firms in terms of investment in other capital. However, given that both the coefficients and the the standard errors are larger, it is possible that my test may have low statistical power in detecting a significant results in the placebo test. The different results across investment in machines and investment in other capital support the view that machines, in contrast to other capital, are closely related to routine-task labor.

[TABLE 5 HERE]

B.2. Routine-Task Employment and Aggregate Shocks

Here, I show that high-*RShare* firms lay off disproportionately more routine-task labor than low-*RShare* firms when aggregate shock is low. Measuring changes in routine-task labor at the firm level is difficult due to data limitations. Specifically, given that the OES

test using recessions as productivity shocks and analyze the high-*RShare* and low-*RShare* firms' investment in machines before and after the shocks in the Internet Appendix. I find that the changes in high-*RShare* firms' investment in machines are significantly more positive than the changes in low-*RShare* firms' investment in machines in 1 year, 2 years, or 3 years after recessions.

³⁷Other capital is the difference between property, plant, and equipment at cost (Compustat item PPEGT) and machinery and equipment at cost (FATE). Investment in other capital is the real growth rate of other capital.

survey covers the same establishment every three years, a firm’s routine-task labor in a given year is measured based on the firm’s establishments that appear in the OES sample both in the current year and over the prior two years. Hence, the year-over-year changes in a firm’s routine-task labor captures the actual hiring and firing of routine-task labor in only one-third of its establishments, since the firm’s routine-task labor in the current year and the following year are constructed using the same OES observations in the overlapping periods.

To avoid the above concern, I conduct the analysis at the establishment level. There are two advantages of using establishment-level data in this analysis. First, doing so overcomes the overlapping-periods issue associated with a firm-level analysis. Second, the establishment-level data provide more detailed information than the firm-level data, such as establishments’ location, which is helpful for controlling for local labor-market heterogeneity.

I construct three proxies of establishments’ change in routine-task employment. The first measure is the change in establishments’ routine-task employment from three years before to the current year normalized by their total number of employees three years before. The second measure is the change in establishments’ *RShare* constructed based on employment in each occupation instead of total wage expense following equation (24) from three years before to the current year. The third measure is the change in establishments’ *RShare* from three years before to the current year. In constructing each of the three measures, routine-task labor both in the current year and three years before is defined based on the RTI score distribution in the economy three years before. Aggregate shocks in this analysis are defined as the real growth in GDP value added from three years before to the current year.

Panel A of Table 6 reports the results of the following panel regression:

$$\begin{aligned}
 Chg_{e,f,t-3,t}^{Routine} = & b_0 + b_1 RShare_{e(f),t-3} + b_2 RShare_{e(f),t-3} \times Shock_{t-3,t} \\
 & + F_f + F_{Ind \times Year} + F_{State \times Year} + \epsilon_{e,f,t},
 \end{aligned} \tag{26}$$

where $Chg_{e,f,t-3,t}^{Routine}$ is one of the three proxies of the change in routine-task employment in firm f ’s establishment e from year $t - 3$ to year t , $RShare_{e(f),t-3}$ is the establishment or its parent firm’s *RShare* in year $t - 3$, $Shock_{t-3,t}$ is the aggregate shock from $t - 3$ to t , and F_f , $F_{Ind \times Year}$, and $F_{State \times Year}$ denote the firm, industry-year, and state-year fixed effects, respectively. While industry-year fixed effects control for intrinsic production technology in terms of routine-task input and non-routine-task input, state-year fixed effects control for the

time-varying effect of local labor market conditions, such as state labor laws, or fluctuations in local wages (see [Tuzel and Zhang \(2015\)](#)).³⁸

In Column (1) of Panel A in Table 6, we see that high-*RShare* firms are more likely to reduce routine-task labor in their establishments than low-*RShare* firms when aggregate shocks are low. Columns (3) and (5) further shows that reduction in routine-task labor during bad times is disproportionately higher in establishments of high-*RShare* firms than low-*RShare* firms. Hence, high-*RShare* firms respond to unfavorable aggregate shocks by undertaking a structural change in their production inputs that narrows their *RShare* gap with low-*RShare* firms.

It is possible that different establishments within a firm may have different *RShare*. In addition, [Giroud and Mueller \(2015\)](#) show that firms reallocate capital and labor among establishments within the firms when facing investment opportunities. To check whether firms are indeed replacing their routine-task labor in high-*RShare* establishments, I use the establishment's *RShare* in Columns (2), (4), and (6) as the independent variable. I find that high-*RShare* establishments respond to unfavorable macroeconomic shocks by reducing more routine-task labor and lowering both of their employment-based *RShare* and *RShare*. These results show that my results are robust to within-firm resource reallocation.

These results, together with the previous results on firms' investment in machines, support my model's prediction that high-*RShare* firms have more switching options to replace routine-task labor with machines when facing unfavorable aggregate shocks.

My model suggests that in response to a favorable aggregate shock, high-*RShare* firms are more likely to undertake new unautomated projects that increase their establishments' *RShare*. I test this prediction by examining the *RShare* of newly opened establishments in high-*RShare* firms and low-*RShare* firms. An establishment is identified as newly opened in a given year if it does not exist in the prior year of the QCEW data, which cover the universe of establishments in the U.S. from 1990 to 2014.³⁹

³⁸Examples of state labor laws that could affect firm decisions are wrongful-discharge laws (see [Serfling \(2015\)](#)) and right-to-work laws (see [Matsa \(2010\)](#) and [Chen, Kacperczyk, and Ortiz-Molina \(2011\)](#)).

³⁹QCEW draws establishment information from the unemployment insurance (UI) agency. Employers of new establishments are required by law to report to UI and pay unemployment taxes if: (1) they pay wages to employees totaling \$1,500 or more in any quarter of a calendar year, or (2) they had at least one employee during any day of a week during 20 weeks in a calendar year, regardless of whether or not the weeks were consecutive. For more details see <http://workforcesecurity.doleta.gov/unemploy/uitaxtopic.asp>

Panel B of Table 6 reports results of the following panel regression:

$$\begin{aligned}
 RShare_{e,f,t}^{Est,(Emp)} = & b_0 + b_1 RShare_{f,t-1} + b_2 RShare_{f,t-1} \times Shock_t \\
 & + F_f + F_{Ind \times Year} + F_{State \times Year} + \epsilon_{e,f,t},
 \end{aligned}
 \tag{27}$$

where $RShare_{e,f,t}^{Est,(Emp)}$ is the $RShare$ or the employment-based $RShare$ of establishments in year t , $RShare_{f,t-1}$ is the $RShare$ of the establishment's parent firm's $RShare$ in year $t - 1$, $Shock_t$ is the real growth rate of GDP value added in year t , and F_f , $F_{Ind \times Year}$, and $F_{State \times Year}$ denote the firm, industry-year, and state-year fixed effects, respectively. The results show that a positive and significant estimation of b_2 , implying that in response to favorable aggregate shocks, high- $RShare$ firms are more likely to hire routine-task labor in their new establishments than low- $RShare$ firms.

[TABLE 6 HERE]

C. Asset Prices

My model implies that high- $RShare$ firms have lower exposure to systematic risk and expected returns. I test this implication below.

C.1. Portfolio Analysis

I explore firms' stock returns using portfolio analysis. Specifically, at the end of each June, firms in each Fama-French 17 industry are sorted into five equally weighted portfolios based on their share of routine-task labor, $RShare$. From Panel B of Table 4, $RShare$ varies from 0.02 for the lowest quintile portfolio to 0.39 for the highest quintile portfolio on average.

In Panel A of Table 7, I find that excess returns monotonically decrease from the lowest $RShare$ quintile to the highest $RShare$ quintile, yielding an average of -3.1% return spread per year. The Sharpe ratio for the long-short portfolio is 0.11, which is lower than that for anomalies that cannot be explained by market risk, such as the value premium, which has a Sharpe ratio of 0.39 (see, for example, Zhang (2005)).

My model assumes that firms are all-equity financed. In practice, firms may also issue debt to finance their investment. If firms issue debt to finance their labor-technology substitution, low- $RShare$ firms are expected to have higher financial leverage and, in turn, higher

returns. To address this concern, I first show in Panel B of Table 4 that low-*RShare* firms have lower financial leverage than high-*RShare* firms, on average. To further address potential time-varying financial leverage between low-*RShare* and high-*RShare* firms, I calculate firms' unlevered returns following the simple approach by Donangelo (2014), and conduct the portfolio analysis using the excess unlevered returns. The unlevered returns are calculated according to

$$R_{f,m,y}^{Unlevered} = RF_{m,y} + (R_{f,m,y}^{Raw} - RF_{m,y}) (1 - Mkt.Lev_{f,y-1}), \quad (28)$$

where $R_{f,m,y}^{Raw}$ is the monthly stock return of firm f in month m of year y , $RF_{m,y}$ is the one-month Treasury bill rate in month m of year y , and $Mkt.Lev_{f,y-1}$ is the market leverage ratio for firm f at the end of year $y - 1$.

Panel B of Table 7 reports the results of excess unlevered returns and the two corresponding market betas for firms in five *RShare* portfolios sorted within industry. Similar to the results using raw excess returns, the portfolio that longs the highest *RShare* portfolio and shorts the lowest *RShare* portfolio observes negative and significant return spreads, indicating that financial leverage is not driving the main results.

In my model, firms' *RShare* and other characteristics such as size and book-to-market are interrelated. Hence, my model does not claim that *RShare* predicts cross-sectional risk and returns after controlling for firms' other characteristics. Nevertheless, as a robustness check, I repeat the portfolio analysis using stock returns adjusted for firm characteristics following Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW). I construct the DGTW-adjusted returns by taking the difference between stocks' raw returns and the benchmark portfolio's returns. The benchmark portfolio is constructed by sequentially sorting all common stocks in the CRSP universe into 125 portfolios based on size, industry-adjusted book-to-market, and momentum (see Daniel, Grinblatt, Titman, and Wermers (1997) for more details).

Panel C shows that the relations between *RShare* and firms' exposure to systematic risk and expected returns are robust to adjusting returns with the characteristics-based benchmarks.

[TABLE 7 HERE]

C.2. CAPM Betas

I explore firms' exposure to systematic risk, proxied by unconditional and conditional market betas under the CAPM framework. Table 8 shows that both of the two market betas decrease monotonically with *RShare*. A portfolio that longs the highest *RShare* portfolio and shorts the lowest *RShare* portfolio has an unconditional market beta of -0.23 and a conditional beta of -0.29 , both of which are highly statistically significant. I do not find significant differences in alpha between the high-*RShare* and low-*RShare* quintiles in either unconditional or conditional CAPM, indicating that the excess returns are explained by market betas.⁴⁰

[TABLE 8 HERE]

C.3. Panel Regressions

In my model, other firm characteristics, most prominently operating leverage and cash flows, are closely related to firms' share of routine-task labor. At the same time, each characteristic captures different firm attributes, with *RShare* most directly related to the value of firms' switching options to replace routine-task labor with machines. In this section, I control for these characteristics directly in panel regressions as follows:

$$\begin{aligned}\beta_{f,t}^{Cond} &= b_0 + b_1 RShare_{f,t-1} + b_2 Char_{f,t-1} + F_{Ind \times Year} + \epsilon_{f,t} \\ R_{f,t} - RF_t &= b_0 + b_1 RShare_{f,t-1} + b_2 Char_{f,t-1} + F_{Ind \times Year} + \epsilon_{f,t},\end{aligned}\tag{29}$$

where $\beta_{f,t}^{Cond}$ is the conditional beta, constructed following Lewellen and Nagel (2006) as the sum of the coefficients for the contemporaneous and lagged monthly market returns when regressing firm f 's monthly excess returns on them in year t (also see Dimson (1979)), $R_{f,t} - RF_t$ is the annual excess return of firm f in year t , $RShare_{f,t-1}$ is the share of routine-task labor of firm f in year $t - 1$, $Char_{f,t-1}$ are the other firm characteristics in year $t - 1$, and $D_{Ind \times Year}$ denotes the industry-year fixed effects.

High-*RShare* firms may have higher operating leverage than low-*RShare* firms, given

⁴⁰In the Internet Appendix, I decompose the market betas for each portfolio into cash flow betas and discount rate betas following Campbell and Vuolteenaho (2004), and find that cash flow betas account for slightly more than half of the market betas, providing supporting channels through which market betas explain excess returns in my test.

that routine-task labor is more costly to use than machines. This channel leads to a positive relation between *RShare* and firm risk, which goes against my main channel and hence works against finding significant results. Table 9 shows that *RShare* is a robust predictor of conditional beta (in Panel A) and future annual excess returns (in Panel B) after controlling for operating leverage as constructed following Novy-Marx (2011).

Cash flows affect firm risk in a more subtle way in my model. The fact that high-*RShare* firms have automated fewer of their unautomated projects than low-*RShare* firms indicates that high-*RShare* firms may have experienced higher idiosyncratic shocks to their projects' cash flows in the past. Given that the shocks are persistent, these firms may be expected to keep earning higher cash flows in the future, making their value less sensitive to negative systematic shocks and thus less risky. To address this alternative channel, I control for firms' cash flows in the panel regressions and find that *RShare* continues predict firms' conditional beta and future annual excess returns.

I also test the predictive power of *RShare* by controlling for firms' market leverage, size, and book-to-market; and I find that *RShare* persistently predicts firms' conditional betas and annual excess returns. Controlling for all firm characteristics, the results show that a one standard deviation decrease in *RShare* (16% in Table 4) increases a firm's expected return by 1.4% ($16\% \times 8.69\%$) per year. Finally, I run the panel regression across all firms, instead of within industry, and find that the coefficient for *RShare* becomes more economically significant compared to when industry fixed effects are added. Hence, my results, based on the within-industry analysis, provide a conservative estimation of the relation between *RShare* and firms' systematic risk and expected returns.

[TABLE 9 HERE]

In Table 10, I present my main return regression results under various assumptions for the correlation structure of the residuals. In the first four columns, I double-cluster the standard errors by year and firm following Petersen (2009). In the last two columns, I run monthly cross-sectional regressions of future excess returns on *RShare*, firm-level control variables, and with and without industry dummies; and I report time series average of the coefficients (Fama and MacBeth (1973)). I find that the results are robust to these alternative specifications.

In summary, the robustness tests above strengthen the interpretation of *RShare* as a

proxy for the value of firms' options to replace routine-task labor with machines.

[TABLE 10 HERE]

C.4. Measurement Error in RShare

I further check whether the results are robust to measurement error in *RShare*. A firm's *RShare* is calculated based on the occupational composition of its establishments that have the same EIN as in the firm's annual report. In practice, a firm may have multiple EINs. Most of such cases occur when the firm operates in multiple states and has different EINs for different states. The EINs in firms' annual reports are usually the EINs of the firms' headquarters. Hence, my *RShare* measure is likely to capture the labor composition for establishments in the states where the firm's headquarters is located. It is not obvious to see whether measurement error in *RShare* due to this reason is likely to create a biased estimation of its stock return predictability. However, measurement error, if it exists, is likely to attenuate the significance of my estimation. I confirm these conjectures using subsample analysis.

In Panel A of Table 11, I examine the predictability of *RShare* on annual stock returns in two subsamples. In one subsample, the ratio of firms' total number of employees, identified in the OES microdata, to that in the Compustat data is below the median ratio of the year. In the other subsample, the ratio is above the median. I do not find any sizable difference in the predictability of *RShare* on annual stock returns in these two subsamples. The coefficient of *RShare* is -8.11 when using the former subsample and -9.24 when using the latter subsample, both of which are very close to the coefficient estimated using the full sample, -8.69 . This result indicates that measurement error, investigated without relating directly to firms' geographic dispersion, is not severe.

Given that measurement error in *RShare* is likely to be more severe for firms that operate across multiple states, I further investigate the predictability of *RShare* on stock returns conditional on the dispersion of firms' operation across states. Garcia and Norli (2012) define firms as geographically focused if few state names are mentioned in the firms' annual reports. Garcia and Norli (2012) report that the average state count for the firms in the highest geographical focus quintile is two. I thus classify firms that mention two or fewer

states in their annual reports as geographically focused firms. Panel B shows that *RShare* indeed has a stronger return predictability among geographically focused firms than among geographically dispersed firms, suggesting that measurement error in *RShare* is less severe among geographically focused firms. Nevertheless, the return predictability of *RShare* is still highly significant among geographically dispersed firms.

In addition, [Tuzel and Zhang \(2015\)](#) examine establishment locations for over 2,000 public firms in 2014 using the ReferenceUSA data. They find that small firms are much more geographically focused. Hence, I further divide my sample into two groups based on whether the firm’s market capitalization is above or below the median of the year. I find that *RShare* predicts annual stock returns more significantly, both economically and statistically, among small firms than among large firms. In Panel C, the coefficient of *RShare* is -12.77 for small firms and -3.33 for large firms. Hence, measurement error in *RShare* seems to be less severe among small firms, which are likely to operate locally. This finding also indicates that the stock return predictability of *RShare* is driven mostly by small firms.

[TABLE 11 HERE]

C.5. Option Exercise in Recessions

I further examine the connection between firms’ option to replace routine-task labor with machines and their exposure to systematic risk by directly examining the consequences of recessions. My model suggests that after a significant negative aggregate shock, like the shocks that occurred during recessions, high-*RShare* firms replace their routine-task labor with machines to a greater extent than do low-*RShare* firms. Hence, after recessions, high-*RShare* firms exercise more of their switching options, making them more similar to low-*RShare* firms in terms of both their production structures and their market betas.

I confirm this prediction in Table 12. Using the 2001 and 2008-09 recessions, I track the two groups of firms over the four years starting in the year prior to each recession. Specifically, I sort firms in each Fama-French 17 industry into five portfolios based on their *RShare* in the year prior to each recession (i.e., in 2000 or 2007) and hold the portfolio formation constant over the observation period. For each portfolio, I track the ratio of machines to total employment, operating leverage, as well as its market beta. Firms are required to have

non-missing information over all four years to avoid selection bias.

Table 12 shows that the differences between the machine-to-employment ratio of the high-*RShare* firms and low-*RShare* firms narrow from 14 thousand dollars per worker to 11 thousand dollars per worker and become statistically insignificant. Consistent with the model assumption that routine-task labor is more costly to use than machines, the gap in operating leverage between high-*RShare* and low-*RShare* firms narrows by more than 10% and becomes statistically insignificant.

More importantly, the market betas for the two groups of firms are much closer to each other after recessions. This result is consistent with the model prediction that high-*RShare* firms exercise their hedging options relatively more than low-*RShare* firms, which narrows the differences in their exposure to systematic risk.

[TABLE 12 HERE]

IV. Conclusion

Technology continuously changes the way our economy produces. With the arrival of new technology, some human skills are upvalued by better tools, while other skills become redundant and are ultimately replaced by new tools. The adoption of new technology to save labor cost often represents an important way for firms to improve efficiency. However, firms do not always adopt new technology upon its arrival. In deed, as I show in this paper, firms tend to wait until economic downturns to adopt labor-saving technology. This link between technology adoption and the business cycle provides a previously unexplored source of systematic risk and has important implications for the cross-section of stock returns.

To illustrate this point, I develop a dynamic model that shows that a firm's option to replace routine-task labor with machines reduces the firm's sensitivity to unfavorable macroeconomic shocks and thus lowers its exposure to systematic risk. The key insight of my model is that adopting machines takes time, as the firm needs to adapt the technology embodied in the machines to its own projects. During this technology adoption period, the projects' production is interrupted. Hence, it is less costly for the firm to launch labor-technology substitution in bad times than in good times. As a result, in the cross-section, firms with more routine-task labor have more opportunities to improve their value in bad times and

thus have lower exposure to systematic risk.

I present novel empirical evidence that supports the main predictions of the model. Using detailed establishment-occupation level data, I calculate the proportion of a firm's total labor costs that can be potentially eliminated with automation, namely, the share of routine-task labor, for publicly traded firms in the U.S. I find that firms with a high share of routine-task labor respond to unfavorable GDP shocks by investing more in machines and reducing more routine-task labor than their industry peers. Moreover, these firms have significantly lower market betas and future returns than their industry peers.

More generally, this research complements recent studies that explore how technological shocks affect the cross-section of stock returns (see, for example, [Garleanu, Panageas, and Yu \(2012\)](#), [Eisfeldt and Papanikolaou \(2013\)](#), and [Kogan and Papanikolaou \(2014\)](#)). In particular, this paper suggests that firms' decisions to adopt technology are related to the business cycle. Accounting for this link between technology adoption and the business cycle in the study of technological shocks and stock returns would be an interesting direction for future work.

Appendix

A. Proofs

A.1. Value Function of Automated Projects

From the dynamic specification of project's cash flows and the SDF, we have:

$$\begin{aligned} A_{t+s} &= A_t e^{-\theta s} e^{\int_0^s \sigma_a e^{\theta(u-s)} dB_u} \\ \Lambda_{t+s} &= \Lambda_t e^{(-r - \frac{1}{2}\sigma_\Lambda^2)s - \sigma_\Lambda B_{\Lambda s}}, \end{aligned} \quad (\text{A.1})$$

where $\sigma_a = \sqrt{\sigma_x^2 + \sigma_z^2 + \sigma_\epsilon^2}$ and $B_t = \frac{\sigma_x B_{xt} + \sigma_z B_{zt} + \sigma_\epsilon B_{\epsilon t}}{\sigma_a}$.

$$\begin{aligned} V_A(t_0; t) &= E_t \int_0^\infty e^{-\delta s} \frac{\Lambda_{t+s}}{\Lambda_t} [\mathbb{1}_{(t+s > t_0+T)} (A_{t+s} - f) - c_N] ds \\ &= E_t \int_{t'}^\infty A_t e^{-\theta s} e^{v_s} ds - \frac{c_N + e^{-(r+\delta)t'} f}{r + \delta}, \end{aligned} \quad (\text{A.2})$$

where $t' = \max(t_0 + T - t, 0)$ and $v_s = (-\delta - r - \frac{1}{2}\sigma_\Lambda^2)s + \int_0^s (\sigma_x e^{\theta(u-s)} - \sigma_\Lambda) dB_{xu} + \int_0^s \sigma_z e^{\theta(u-s)} dB_{zu} + \int_0^s \sigma_\epsilon e^{\theta(u-s)} dB_{\epsilon u}$, which is a random variable that follows a normal distribution (see [Shreve \(2004\)](#) section 6.9). The mean and variance of v_s are given as

$$\begin{aligned} E(v_s) &= (-\delta - r - \frac{1}{2}\sigma_\Lambda^2)s \\ \text{Var}(v_s) &= \sigma_\Lambda^2 s - \frac{2\sigma_x \sigma_\Lambda}{\theta} (1 - e^{-\theta s}) + \frac{\sigma_a^2}{2\theta} (1 - e^{-2\theta s}). \end{aligned} \quad (\text{A.3})$$

Exchanging the expectation operator and the integral operator in (A.2) using Fubini's Theorem, and using the log-normal property of e^{v_s} , we have

$$\begin{aligned} V_A(t_0; t) &= \int_{t'}^\infty A_t e^{-\theta s} e^{E(v_s) + \frac{1}{2}\text{Var}(v_s)} ds - \frac{c_N + e^{-(r+\delta)t'} f}{r + \delta} \\ &= \int_{t'}^\infty A_t e^{-\theta s} e^{g(s)} ds - \frac{c_N + e^{-(r+\delta)t'} f}{r + \delta}, \end{aligned} \quad (\text{A.4})$$

where $g(s) = (-\delta - r)s - \frac{\sigma_x \sigma_\Lambda}{\theta} (1 - e^{-\theta s}) + \frac{\sigma_a^2}{4\theta} (1 - e^{-2\theta s})$.

Q.E.D.

A.2. Function of Optimal Discounting

Given that the payoff of exercising the switching option is monotonically decreasing in A_t (see equation (12)) and also that the process of A_t exhibits positive serially correlation, we know that the optimal exercise of the switching option is when A_t falls below a certain threshold A^* (see Dixit and Pindyck (1994) section 4.1.D).

In order to calculate $\hat{E}_t[e^{-(r+\delta)\tau}]$, note that the stochastic discount factor uniquely corresponds to a risk-neutral probability measure $\hat{\mathbb{P}}$, under which $\hat{B}_{xt} = B_{xt} + \sigma_\Lambda t$ is a standard Brownian motions. $\hat{\mathbb{P}}$ satisfies

$$\begin{aligned} \frac{d\hat{\mathbb{P}}}{d\mathbb{P}} &= \frac{\Lambda_t}{\Lambda_0} e^{rt} \\ &= \exp\left(-\sigma_\Lambda B_{xt} - \frac{1}{2}\sigma_\Lambda^2 t\right), \end{aligned} \tag{A.5}$$

where \mathbb{P} is the physical probability measure. Given that B_{zt} and $B_{\epsilon t}$ are idiosyncratic, they have the same dynamics under \mathbb{P} and $\hat{\mathbb{P}}$. Let $\hat{a}_t = \log A_t + \frac{\sigma_\Lambda \sigma_x}{\theta}$, then the dynamics of \hat{a}_t under $\hat{\mathbb{P}}$ are

$$d\hat{a}_t = -\theta \hat{a}_t dt + \sigma_a d\hat{B}_t, \tag{A.6}$$

where $\hat{B}_t = \frac{\sigma_x \hat{B}_{xt} + \sigma_z B_{zt} + \sigma_\epsilon B_{\epsilon t}}{\sigma_a}$ is still a standard Brownian motion under $\hat{\mathbb{P}}$. Therefore, τ equals the time passed until \hat{a}_t reaches $\hat{a}^* = \log A^* + \frac{\sigma_\Lambda \sigma_x}{\theta}$ for the first time. Applying the Laplace transform of τ under $\hat{\mathbb{P}}$ (Ricciardi and Sato (1988)), we have

$$\begin{aligned} &\hat{E}_t[e^{-(r+\delta)\tau}] \\ &= \exp\left\{\frac{\left[\left(\log A_t + \frac{\sigma_\Lambda \sigma_x}{\theta}\right)^2 - \left(\log A^* + \frac{\sigma_\Lambda \sigma_x}{\theta}\right)^2\right] \theta}{2\sigma_a^2}\right\} \frac{D_{-(r+\delta)/\theta}\left[\left(\log A_t + \frac{\sigma_\Lambda \sigma_x}{\theta}\right) \sqrt{\frac{2\theta}{\sigma_a^2}}\right]}{D_{-(r+\delta)/\theta}\left[\left(\log A^* + \frac{\sigma_\Lambda \sigma_x}{\theta}\right) \sqrt{\frac{2\theta}{\sigma_a^2}}\right]} \\ &= O(A_t, A^*), \end{aligned} \tag{A.7}$$

in which $D_x(z)$ is a parabolic cylinder function given as

$$D_x(z) = 2^{x/2} \sqrt{\pi} \exp\left(-\frac{z^2}{4}\right) \left\{ \frac{1}{\Gamma\left(\frac{1-x}{2}\right)} H\left(-\frac{x}{2}, \frac{1}{2}; \frac{z^2}{2}\right) - \frac{\sqrt{2}z}{\Gamma\left(-\frac{x}{2}\right)} H\left(\frac{1-x}{2}, \frac{3}{2}; \frac{z^2}{2}\right) \right\}, \tag{A.8}$$

where $\Gamma(x)$ is the Euler gamma function and $H(\alpha, \gamma; z)$ is the Kummer function defined as

$$H(\alpha, \gamma; z) = \sum_{n=0}^{\infty} \frac{(\alpha)_n z^n}{(\gamma)_n n!} \quad (\text{A.9})$$

with $(\eta)_n = \eta(\eta + 1) \cdots (\eta + n - 1)$.

Q.E.D.

A.3. Comparison of Project Risks

I first prove that the beta of the assets in place of an unautomated project, β_U^{AP} , is larger than that of a goods-producing automated project that has the same set of shocks to the unautomated project, β_A . It is easy to see that $V_U^{AP} = V_A - \frac{c_R}{r+\delta}$. Hence, applying the definition of beta in equation (19), we have $\beta_U^{AP} > \beta_A$ for any A_t .

I then prove that the beta of a newly initiated automated project minus investments in machines, β_A^{new} , is lower than a goods-producing automated project, β_A , when $A_t = A^*$. Note that

$$\beta_A^{new} = \frac{\sigma_x}{\sigma_\Lambda} \frac{\int_T^\infty A^* e^{-\theta s} e^{g(s)-\theta s} ds}{\int_T^\infty A^* e^{-\theta s} e^{g(s)} ds - \frac{c_N + e^{-(r+\delta)T} f}{r+\delta} - I_M} \quad (\text{A.10})$$

and

$$\beta_A = \frac{\sigma_x}{\sigma_\Lambda} \frac{\int_0^\infty A^* e^{-\theta s} e^{g(s)-\theta s} ds}{\int_0^\infty A^* e^{-\theta s} e^{g(s)} ds - \frac{c_N + f}{r+\delta}} \quad (\text{A.11})$$

Therefore, the condition for $\beta_A^{new} < \beta_A$ is

$$\frac{\int_T^\infty A^* e^{-\theta s} e^{g(s)-\theta s} ds}{\int_T^\infty A^* e^{-\theta s} e^{g(s)} ds - \frac{c_N + e^{-(r+\delta)T} f}{r+\delta} - I_M} < \frac{\int_0^\infty A^* e^{-\theta s} e^{g(s)-\theta s} ds}{\int_0^\infty A^* e^{-\theta s} e^{g(s)} ds - \frac{c_N + f}{r+\delta}} \quad (\text{A.12})$$

The parameters presented in Table 1 satisfy this condition.

Finally, I provide the equation that determines $\bar{A}(t_0)$. Note that the beta for an unautomated project, $\beta_U(t)$, and an automated project initiated at t_0 , $\beta_A(t_0; t)$, can be expressed

as

$$\begin{aligned}\beta_U(t) &= \frac{\sigma_x \int_0^\infty A_t e^{-\theta s} e^{g(s)-\theta s} ds + P(A^*) \dot{O}(A_t, A^*) A_t}{\sigma_\Lambda V_U(t)} \\ \beta_A(t_0; t) &= \frac{\sigma_x \int_{t'}^\infty A_t e^{-\theta s} e^{g(s)-\theta s} ds}{\sigma_\Lambda V_A(t_0; t)},\end{aligned}\tag{A.13}$$

where $\dot{O}(A_t, A^*) = \frac{dO(A_t, A^*)}{dA_t}$ and $t' = \max(t_0 + T - t, 0)$. Therefore, $\bar{A}(t_0)$ is determined by the following equation:

$$\frac{\int_0^\infty A_t e^{-\theta s} e^{g(s)-\theta s} ds + P(A^*) \dot{O}(A_t, A^*) A_t}{V_U(t)} = \frac{\int_{t'}^\infty A_t e^{-\theta s} e^{g(s)-\theta s} ds}{V_A(t_0; t)}.\tag{A.14}$$

Q.E.D.

B. Simulation Procedure

The process for stochastic discount factor Λ_t , and the shocks, e^{x_t} , e^{z_t} and e^{ϵ_t} are discretized using the following approximations:

$$\begin{aligned}\Lambda_{t+\Delta t} &= \Lambda_t e^{(-r - \frac{1}{2}\sigma_\Lambda^2)\Delta t - \sigma_\Lambda \sqrt{\Delta t} \xi_{x_t}} \\ e^{x_{t+\Delta t}} &= (e^{x_t}) e^{-\theta \Delta t} e^{\sigma_x \sqrt{\frac{1-e^{-2\theta \Delta t}}{2\theta}} \xi_{x_t}} \\ e^{z_{t+\Delta t}} &= (e^{z_t}) e^{-\theta \Delta t} e^{\sigma_z \sqrt{\frac{1-e^{-2\theta \Delta t}}{2\theta}} \xi_{z_t}} \\ e^{\epsilon_{t+\Delta t}} &= (e^{\epsilon_t}) e^{-\theta \Delta t} e^{\sigma_\epsilon \sqrt{\frac{1-e^{-2\theta \Delta t}}{2\theta}} \xi_{\epsilon_t}},\end{aligned}\tag{B.1}$$

where $\Delta t = 1/12$ is one month, and ξ_{x_t} , ξ_{z_t} and ξ_{ϵ_t} are standard normal random variables that are independent with each other and over time.

I specify a grid of 10 points for each of the processes, and linearly interpolate the value functions based on the grids. The grid points are chosen by first specifying an upper bound and lower bound of the state variable and equally spanning the interval.

Profits in each period are thus

$$\begin{aligned}\pi_A(t) &= (A_t - c_N - f)\Delta t \\ \pi_U(t) &= (A_t - c_R - c_N - f)\Delta t.\end{aligned}\tag{B.2}$$

The value of V_A and V_U^{SO} can be easily calculated based on the analytical functional

forms. I calculate A^* by searching a large space of A_t .

The relation between project's value, dividend, profit, and investment is

$$V_t = d_t + E\left(\frac{\Lambda_{t+\Delta t}}{\Lambda_t} V_{t+\Delta t}\right), \quad (\text{B.3})$$

where $d_t = \pi_t - I_t$, and A_t is the state variable.

The value of growth options are calculated following [Berk, Green, and Naik \(1999\)](#), who simulate 400 time periods in order to obtain a good approximation of the integration. I discretize the present value of growth opportunities as

$$PVGO_t = \frac{\lambda \Delta t}{J} \sum_{j=1}^J \sum_{n=1}^{\infty} PVGO_{j,n}, \quad (\text{B.4})$$

where $PVGO_{j,n}$ is the j th realization of the growth opportunity at time $t + s\Delta t$. Note that $n = 0$ is not included here (those opportunities that come up at t are already taken or passed). The growth opportunity counts starting from $t + \Delta t$ on.

C. Sample Construction

Monthly common stock data is from the Center for Research in Security Prices (CRSP share code SHRCD =10 or 11). The sample includes stocks listed on NYSE, AMEX, and NASDAQ. Accounting information is from Standard and Poor's Compustat annual industrial files. Following [Fama and French \(1993\)](#), in order to avoid the survival bias in the data, I include firms in my sample after they have appeared in Compustat for two years. I follow the literature and exclude firms with primary standard industrial classifications between 4900 and 4999 (regulated) and between 6000 and 6999 (financial). I exclude firm-year observations. In every sample year, firm-level accounting variables and size measures are Winsorized at the 1% level (0.5% in each tail of the distribution) to reduce the influence of possible outliers. I also exclude from the sample the lowest 20th size quantile (i.e., 5% of the sample of firms) to avoid anomalies driven by micro-cap firms, as discussed in [Fama and French \(2008\)](#). I aggregate OES establishments to Compustat firms using Employer Identification Number and supplement the matching by using legal names.

I rank firms based on their share of routine-task labor relative to their industry peers as follows. I first categorize firms into 17 industries using the [Fama and French \(1997\)](#)

classification. Within each industry, I sort firms into five portfolios based on their share of routine-task labor in each year. Thus, portfolio L includes firms that are in the bottom quintiles in terms of share of routine-task labor from all industries. Similarly, I construct portfolios 2, 3, 4, and H .

I construct the following variables for firms:

- $RShare$ is firms' share of routine-task labor created following equation (24).
- $Mach/Capital$ is the ratio of machinery and equipment at cost to capital, which is the sum of machinery and equipment at cost (Compustat item FATE) and structures at cost, including building (FATB), construction in progress (FATC), and land and improvements (FATP).
- $Mach/RTL$ is the ratio of machinery and equipment at cost (FATE) to the total number of routine-task labor in the firm, at \$ millions per worker. A firm's total number of routine-task labor is calculated as the total number of routine-task labor of its establishments identified in the microdata, projected to the firm level using total number of employees from Compustat (EMP).
- CF is cash flow defined as earnings before extraordinary items (IB) plus depreciation (DP) and is normalized by capital stock (PPENT) at the beginning of the year following Malmendier and Tate (2005).
- $Stock Ret$ is firms' annual stock returns.
- $Op.Lev$ is firms' operating leverage defined as cost of goods sold (COGS) plus selling, general, and administrative expenses (SGA); and is normalized by total assets (AT) following Novy-Marx (2011).
- $Mkt.Lev$ is firms' financial leverage defined as the proportion of total debt to market value of the firm defined following Fan, Titman, and Twite (2012). Total debt is the book value of short-term (DLC) and long-term interest bearing debt (DLTT). Market value of the firm is the market value of common equity plus book value of preferred stock (PSTK) plus total debt. Market value of common equity is defined as in Fama and French (1992).
- $Size$ and B/M are the natural logarithms of firms' market value and firms' book-to-market, respectively, defined following Fama and French (1992).
- I^M is firms' investment in machines, calculated as the ratio of the current year's machinery and equipment at cost (FATE) to the previous year's machinery and equipment

at cost minus one.

- I^S is firms' investment in structures, calculated as the ratio of current year's structures at cost to the previous year's structures at cost minus one. Firms' structures at cost is the sum of building (FATB), construction in progress (FATC), and land and improvements (FATP) at cost.
- *Shock*: Real growth rate of GDP value added.
- *Tobin's Q* is firms' Tobin's Q defined as the ratio of firms' market value, the sum of total liability (LT) and market equity, to total assets (AT). Market equity is defined as in [Fama and French \(1992\)](#).
- *Cash Holding* is firms' cash holding defined as cash and short-term investments (CHE), normalized by total assets (AT).
- *Asset* is firms' total assets (AT).

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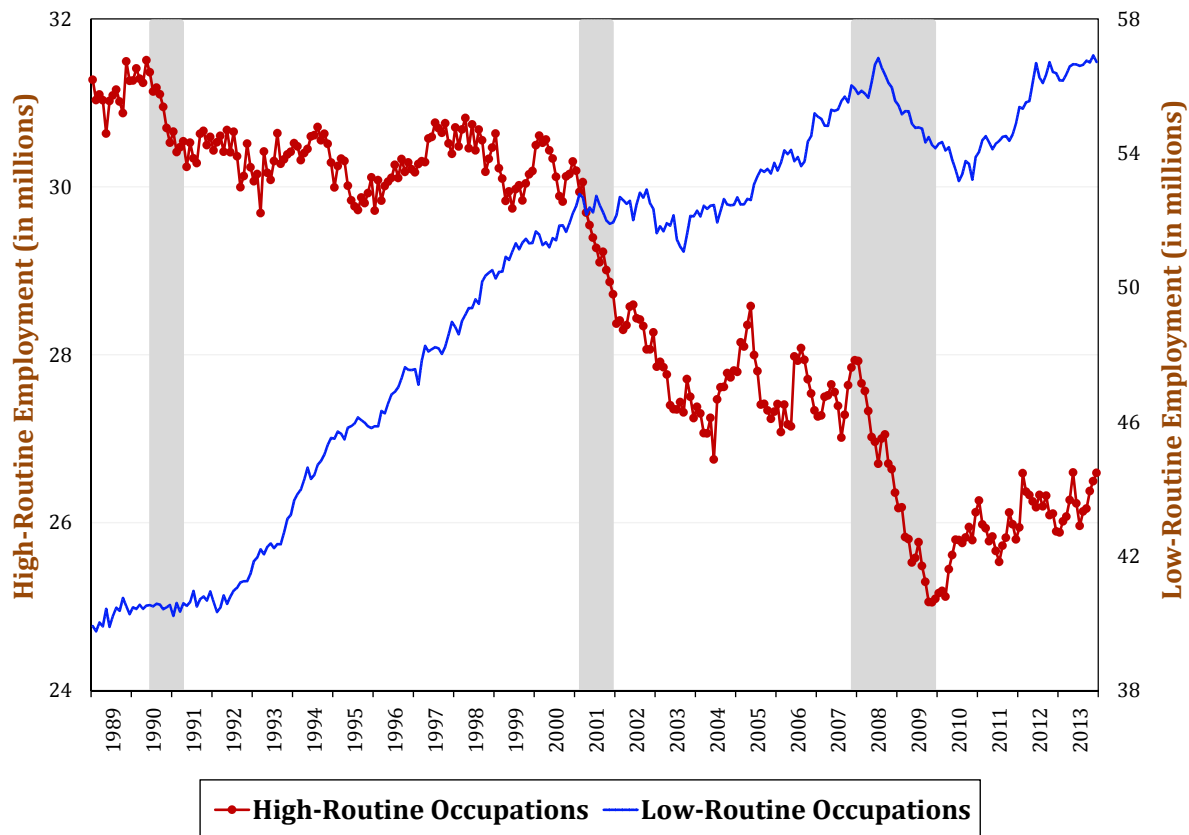
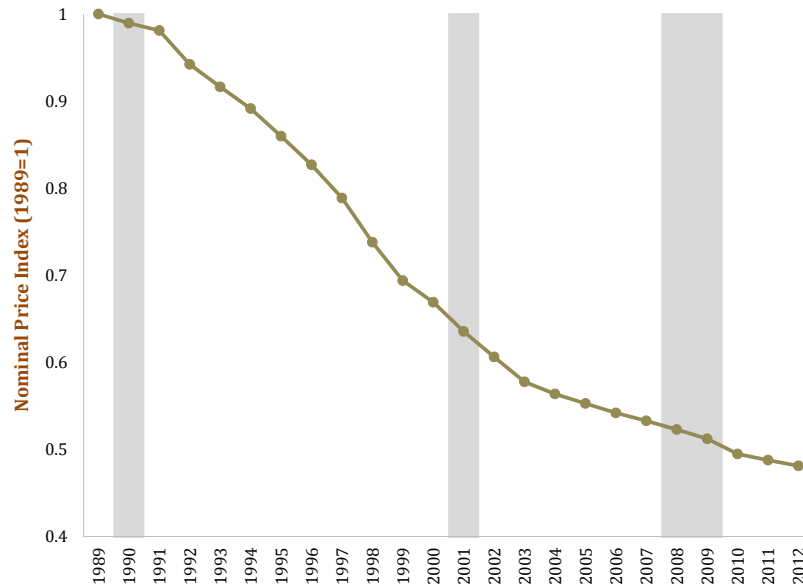


Figure 1. Monthly employment of high-routine occupations and low-routine occupations. This figure illustrates the monthly employment of routine-task labor and non-routine-task labor using the Current Population Survey (CPS) monthly basic data. The left axis corresponds to the employment of routine-task labor, and the right axis corresponds to the employment of non-routine-task labor. I crosswalk the occupation classifications of different years to a unified occupation classification *occ1990*, which is available at the Integrated Public Use Microdata Series at the University of Minnesota. Following Autor and Dorn (2013), I obtain the task skill data from the Dictionary of Occupation Titles, fourth edition and revised fourth edition, and calculate the routine-task intensity (*RTI*) score for each *occ1990* occupation as in equation (23). I classify an occupation as *High-Routine Occupation* or *Low-Routine Occupation* if its *RTI* score is in the bottom or top 30% of the *RTI* distribution in the 1980 Census. The monthly employment is aggregated from the number of individuals in the occupations, weighted by CPS sampling weights, and seasonally adjusted using the Census X12 ARIMA. The shaded areas indicate the NBER recession months.

Panel A. Quality-Adjusted Price of Equipment and Software



Panel B. Hourly Wage of High-Routine Occupations and Low-Routine Occupations

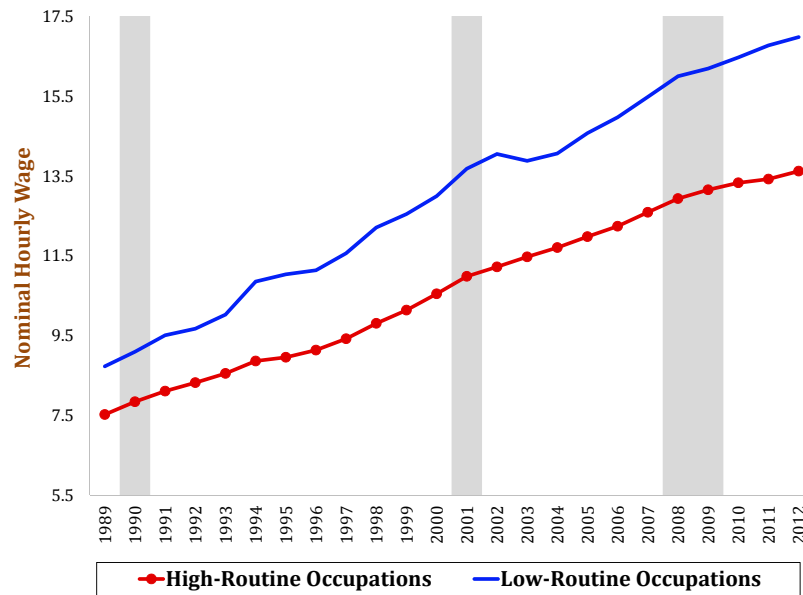
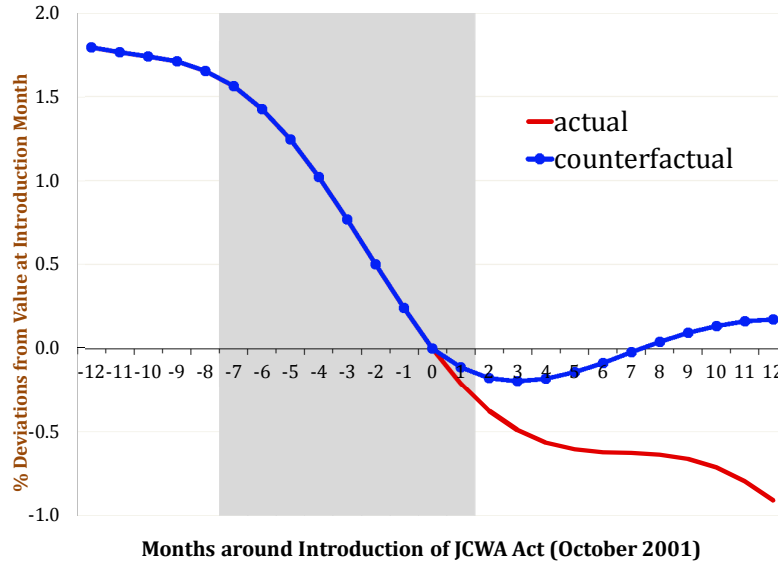


Figure 2. Time-series of machine price and wages. Panel A presents the quality-adjusted price of equipment and software provided by Ryan Isaelson. The price index is aggregated from the price of 22 groups of durable equipment and software presented by the Bureau of Economic Analysis. These data are first constructed by [Gordon \(1990\)](#) and later extended by [Israelson \(2010\)](#). Panel B presents the hourly wage of occupations by routine-task intensity score. The nominal hourly wage for each occupation is the average hourly wage of individuals in that occupation, weighted by the sample personal earnings weights, from the sample of the Current Population Survey Outgoing Rotation Group maintained by the National Bureau of Economic Research. See [Figure 1](#) for definitions of high-routine occupations and low-routine occupations. The shaded areas indicate recession years.

Panel A. Actual and Counterfactual Employment of High-Routine Occupations



Panel B. Actual and Counterfactual Employment of Low-Routine Occupations

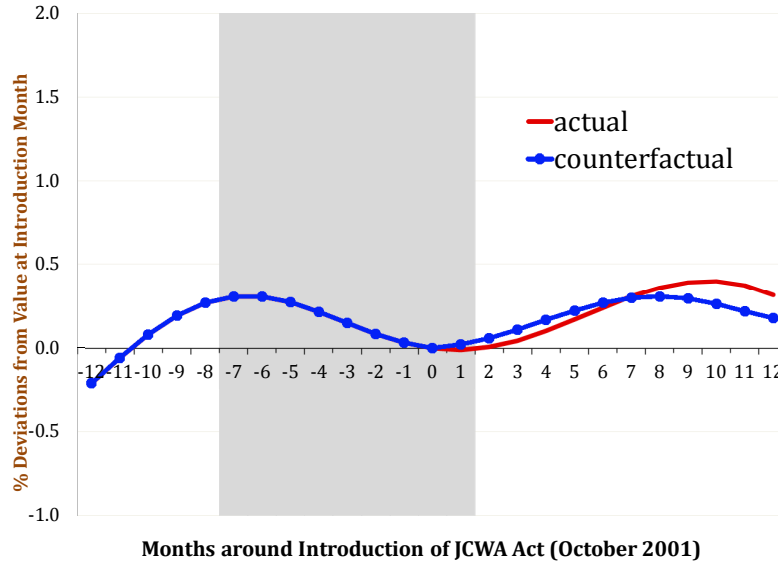


Figure 3. Actual and counterfactual employment of high-routine occupations and low-routine occupations around the Job Creation and Worker Assistance Act of 2002. The Job Creation and Worker Assistance Act of 2002 (*JCWA Act*) was introduced on October 11, 2011. Its first passage vote took place on October 24, 2011, and it was signed by President George W. Bush on March 9, 2002. The *JCWA Act* offers a 30% tax bonus on new qualified property, mostly machinery and equipment, that is acquired by companies after September 10, 2011 and placed in service before September 11, 2004. The actual employment is from October 2000 to October 2002. Following [Jaimovich and Siu \(2014\)](#), I construct counterfactual data by pairing July 1990 and March 2001 which are the starting months of the recessions of 1990 and 2001 according to the National Bureau of Economic Research, respectively. I rescale the counterfactual series to match the magnitude of the fall in actual employment from the starting month of the 2001 recession to the month in which the *JCWA Act* was introduced. The monthly employment series of high-routine occupations and low-routine occupations are described in Figure 1. These series are further logged and band-pass filtered to remove fluctuations at frequencies higher than 12 months. The shaded area indicates the NBER recession months.

Table 1
Parameter Values and Target Moments

Panel A presents the parameter values used in the model simulation. Panel B presents the moments used to pinpoint some of the parameter values. A firm's share of routine-task labor is the ratio of the total wage expense on its routine-task labor relative to its total wage expense, as defined in equation (6). Aggregate share of routine-task labor is calculated based on the firm sample from 1990 to 2014 (see Section II for details). Aggregate gross investment is the total real investment in fixed assets normalized by the previous year's real fixed assets, using data from the Standard Fixed Assets Tables provided by the Bureau of Economic Analysis. GDP growth is the real growth rate of GDP value added. Aggregate gross hiring is the ratio of the total real earnings of the new hires of stable jobs in the current quarter to the total real earnings of the stable jobs in the last quarter, and annualized by multiplying by 4, using data from the Quarterly Workforce Indicators provided by the Census Bureau.

Panel A: Parameter Values				
Parameters	Symbol	Value	Source	
<i>Technology</i>				
Volatility of aggregate shock	σ_x	0.13	Kogan and Papanikolaou (2014)	
Volatility of firm-specific shock	σ_z	0.20	Kogan and Papanikolaou (2014)	
Volatility of project-specific shock	σ_ϵ	1.50	Kogan and Papanikolaou (2014)	
Rate of mean reversion	θ	0.35	Kogan and Papanikolaou (2014)	
<i>Project</i>				
Operating cost except for wage expense	f	2.05	Matching moments	
Total wages for non-routine-task labor	c_N	0.25	Matching moments	
Total wages for routine-task labor	c_R	0.45	Matching moments	
Investment for project initiation	I	3.90	Matching moments	
Investment in machines per automated project	I_M	0.50	Matching moments	
Required time for technology adoption	T	0.75	Kydland and Prescott (1982)	
Project obsolescence rate	δ	0.10	Kogan and Papanikolaou (2014)	
Project arrival rate	λ	12	Matching moments	
<i>Stochastic discount factor</i>				
Risk-free rate	r	0.025	Kogan and Papanikolaou (2014)	
Price of risk of aggregate shock	σ_Λ	1.30	Matching moments	
Panel B: Moments				
Moments			Data	Model
<i>Aggregate economic moments</i>				
Mean of aggregate dividend growth			0.02	0.02
Aggregate share of routine-task labor			0.14	0.14
Correlation between gross investment and GDP Growth			0.64	0.54
Correlation between gross hiring and GDP Growth			0.74	0.69
<i>Asset pricing moments</i>				
Mean of equal-weighted aggregate risk premium			0.13	0.13

Table 2
Five Portfolios Sorted on $RShare$ using Model Simulated Data

This table shows the asset pricing tests for five portfolios sorted on share of routine-task labor ($RShare$) using model simulated data. A firm's $RShare$ is the ratio of the total wage expense on its routine-task labor relative to its total wage expense, as defined in equation (6), and is lagged by one year. Excess returns are annualized by multiplying by 12 and reported in percentages. $MKT \beta$ is the coefficient of regressing the excess returns of the portfolio on the excess returns of the market portfolio. Standard errors are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

	L	2	3	4	H	H-L
$E[R] - r_f$ (%)	14.20*** (1.62)	13.60*** (1.59)	12.94*** (1.45)	12.27*** (1.39)	11.96*** (1.32)	-2.24*** (0.29)
MKT β	1.13*** (0.00)	1.08*** (0.00)	1.02*** (0.00)	0.96*** (0.00)	0.95*** (0.00)	-0.18*** (0.00)
$RShare$	0.06	0.11	0.14	0.18	0.22	0.17

Table 3
Routine-Task Labor

Panel A presents the time-series average of the share of routine-task labor for aggregate occupational groups using establishment-occupation level data provided by Occupational Employment Statistics program of the Bureau of Labor Statistics. Routine-task labor (*RTL*) is defined as workers in occupations with routine-task intensity scores in top quintile of the distribution in that year. See Section II for the definition of routine-task intensity score. *Emp in 2014* is the total employment in millions as of the year 2014. The aggregate occupational group is defined as the major group, following the OES Taxonomy classification for the sample of 1990-1998. For the 1999-2014 sample, which uses the Standard Occupational Classification (SOC) classification for occupations, I aggregate the major SOC classification to seven aggregate groups following the suggestions of the SOC Revision Policy Committee. *Management* represents managerial and administration occupations (SOC 11-13). *Professional* represents professional, paraprofessional, and technical occupations (SOC 15-31). *Sales* represents sales-related occupations (SOC 41). *Clerk* presents clerical, office and administrative support occupations (SOC 43). *Service* represents service and related occupations (SOC 33-39). *Agriculture* represents farming, fishing, and forestry occupations (SOC 45). *Production* represents production, maintenance, construction, and transportation occupations (SOC 47-53). Panel B presents the time-series average of the correlation between different characteristics of occupations. *Routine-task labor* is a dummy variable that equals one if the occupation is routine-task labor during that year. *RTI Score* is the routine-task intensity score of the occupation. *Offshorability*, created by Acemoglu and Autor (2011), is the propensity of the occupation to be outsourced to foreign countries. *Wage* is the median hourly wage of the occupation. *Skill* is the Specific Vocational Preparation measure from the Dictionary of Occupational Titles, which measures the occupation’s required level of specific preparation. *Unionization* is the percentage of workers in the occupation covered by unions from www.unionstats.com. Panel B is prepared using OES data from 1999-2014 under SOC classification.

Panel A: Routine-Task Labor in Occupation Groups								
	Management	Professional	Sales	Clerk	Service	Agriculture	Production	Total
RTL (%)	0.2%	5.6%	22.2%	32.0%	36.1%	8.3%	20.4%	20.0%
Emp in 2014	4.96	11.42	7.84	4.39	7.47	0.16	9.23	45.46

Panel B: Average Correlation Matrix							
	Routine-Task Labor	RTI Score	Offshorability	Wage	Skill	Unionization	
Routine-Task Labor	1						
RTI Score	0.65	1					
Offshorability	-0.02	-0.06	1				
Wage	-0.28	-0.35	0.12	1			
Skill	-0.27	-0.44	0.05	0.64	1		
Unionization	-0.05	-0.07	-0.25	0.00	-0.06	1	

Table 4
Summary Statistics of Firms

This table presents the summary statistics. Panel A reports the mean and standard deviation of share of routine-task labor (*RShare*) for all matched Compustat firms by industrial sectors from 1990 to 2014. *RShare* is the ratio of a firm's total wage expense on its routine-task labor to its total wage expense, as defined in equation (24). Sector is at the SIC division level. Panel B reports the characteristics of firms sorted into five portfolios based on their *RShare* within industry. Each year, firms in each of the Fama-French 17 industries are sorted into five portfolios based on their *RShare*. *Mach/Capital* is the ratio of machinery and equipment at cost to capital at cost (i.e., machinery and equipment at cost plus structures at cost). *Mach/RTL* is the ratio of machinery and equipment at cost to total number of routine-task labor in the firm in million dollars per employee. *Op.Lev* and *CF* represent firms' operating leverage and cash flow, respectively. *Size*, *B/M*, and *Mkt.Lev* represent the market capitalization, book-to-market, and financial leverage, respectively. All variables are winsorized at the 1% level (0.5% in each tail of the distribution). See the Appendix for definitions of firm-level variables. Panel C shows the year-over-year transition probability matrix of a firm moving from one *RShare* quintile to another. *RShare* quintiles are sorted within Fama-French 17 industries.

Panel A: <i>RShare</i> in Compustat Firms											
Sector	Agricult	Mining	Construct	Manuf	Transp	Wholesale	Retail	Finance	Service	Admin	Total
Mean	0.13	0.12	0.07	0.17	0.10	0.15	0.24	0.14	0.11	0.13	0.15
Std	0.14	0.15	0.11	0.16	0.11	0.14	0.19	0.16	0.15	0.16	0.16
N	224	3,379	969	40,581	10,258	3,589	7,733	11,763	17,189	738	96,423

Panel B: Firm Characteristics in Portfolios Sorted by <i>RShare</i> within Industry									
Quintiles	RShare	Mach/Capital	Mach/RTL	Op.Lev	CF	Size	B/M	Mkt.Lev	
1	0.02	0.78	3.73	1.06	-0.25	12.77	0.63	0.17	
2	0.06	0.74	1.27	1.07	0.13	13.08	0.64	0.20	
3	0.12	0.72	0.61	1.13	0.28	13.11	0.67	0.22	
4	0.20	0.71	0.35	1.20	0.32	13.10	0.69	0.23	
5	0.39	0.70	0.17	1.27	0.40	12.78	0.72	0.23	

Panel C: Transition Probabilities across Portfolios Sorted by <i>RShare</i> within Industry						
Current Year	Next Year					
	L	2	3	4	H	
1	0.70	0.19	0.05	0.03	0.03	
2	0.14	0.62	0.18	0.04	0.02	
3	0.04	0.14	0.60	0.18	0.04	
4	0.02	0.03	0.15	0.63	0.16	
5	0.02	0.02	0.04	0.15	0.76	

Table 5
Response of Firm Investment to Aggregate Shocks

This table shows the response of investment in machinery capital (main test) and other capital (placebo test) to aggregate shocks for firms with different shares of routine-task labor, $RShare$. The sample period is 1990-2014 for all columns except for Columns (3) and (4), which exclude 2002-2004 to rule out the impact of the Job Creation and Worker Assistant (JCWA) Act of 2002 which provides a tax bonus on corporate investment in equipment (see Section B.4 for more details). The dependent variables are *Investment in Machines*, which is the real growth rate of machinery and equipment at cost (Compustat item FATE), and *Investment in Other Capital*, which is the real growth rate of property, plant, and equipment at cost except for machinery and equipment at cost (PPEGT - FATE). *Shock* is the growth rate of real GDP value added. See the Appendix for definitions of firm-level variables. All standard errors are clustered at the firm level and reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Dep. Var.	Investment in Machines				Investment in Other Capital	
	(1)	(2)	(3)	(4)	(5)	(6)
$RShare_{t-1}$	0.041** (0.021)	0.037* (0.020)	0.043** (0.022)	0.038* (0.021)	0.029 (0.048)	0.013 (0.047)
$RShare_{t-1} \times Shock_t$	-1.299** (0.643)	-1.166** (0.547)	-1.510** (0.684)	-1.507** (0.648)	-1.909 (1.385)	-1.333 (1.362)
Log Tobin's Q_{t-1}		0.127*** (0.007)		0.128*** (0.008)		0.203*** (0.017)
Mkt.Lev $_{t-1}$		-0.222*** (0.018)		-0.222*** (0.019)		-0.266*** (0.041)
Cash Flow $_{t-1}$		0.000 (0.001)		0.000 (0.001)		0.004 (0.003)
Cash Holding $_{t-1}$		0.305*** (0.028)		0.337*** (0.031)		0.741*** (0.073)
Log Asset $_{t-1}$		-0.022*** (0.005)		-0.027*** (0.006)		-0.067*** (0.013)
Firm FE	Y	Y	Y	Y	Y	Y
Ind \times Year FE	Y	Y	Y	Y	Y	Y
Observations	38,616	38,616	33,248	33,248	37,808	37,808
Adjusted R^2	0.355	0.406	0.384	0.436	0.312	0.340

Table 6

Response of Establishment Routine-Task Employment to Aggregate Shocks

Panel A shows the response of routine-task employment changes to aggregate shocks at the establishment level. $Chg. Emp_{t-3,t}^R$ is the establishment's 3-year change in employment of routine-task labor normalized by the total number of employees three years earlier. $Chg. RShare_{t-3,t}^{Est,Emp}$ and $Chg. RShare_{t-3,t}^{Est}$ are the 3-year changes in the establishment's employment-based share of routine-task labor and share of routine-task labor, respectively. An establishment's (employment-based) share of routine-task labor is the ratio of its (employment of routine-task labor) wage expense on its routine-task labor to its (total employment) total wage expense. In all variable constructions, routine-task labor is defined at $t - 3$ and maintains the same definition for three years to form the time-series changes of the variables. $RShare_{t-3}$ is the establishment's parent firm's $RShare$ three years before in Columns (1), (3), and (5); and the establishment's $RShare$ three years before in Columns (2), (4), and (6). $Shock_{t-3,t}$ is the growth rate of real GDP value added from $t - 3$ to t . Ind is the Fama-French 17 industry classification. $State$ is the state in which the establishment is located. Panel B reports the response of routine-task employment to aggregate shocks in newly opened establishments. An establishment is identified as newly opened in year t if it does not exist in the Quarterly Census of Employment and Wages database in year $t - 1$ but exists in year t . $RShare_t^{Est,Emp}$ and $RShare_t^{Est}$ are the establishment's employment-based share of routine-task labor and share of routine-task labor, respectively. $RShare_{t-1}$ is the parent firm's $RShare$ in year $t - 1$. $Shock_t$ is the growth rate of real GDP value added in year t . Standard errors, reported in parentheses, are clustered at the firm level in all cases except for Columns (2), (4), and (6) in Panel A, which are clustered at the establishment level. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. The sample period is 1996-2014 for Panel A, and 1990-2014 for Panel B.

Panel A: Existing Establishments						
Dep. Var.	Chg. $Emp_{t-3,t}^R$		Chg. $RShare_{t-3,t}^{Est,Emp}$		Chg. $RShare_{t-3,t}^{Est}$	
<i>Level of $RShare_{t-3}$:</i>	Firm	Est.	Firm	Est.	Firm	Est.
	(1)	(2)	(3)	(4)	(5)	(6)
$RShare_{t-3}$	-0.941*** (0.082)	-0.851*** (0.015)	-0.802*** (0.065)	-0.840*** (0.009)	-0.716*** (0.061)	-0.761*** (0.009)
$RShare_{t-3}$ $\times Shock_{t-3,t}$	1.453* (0.764)	0.421** (0.189)	0.919** (0.446)	0.548*** (0.111)	0.758** (0.385)	0.335*** (0.102)
Firm FE	Y	Y	Y	Y	Y	Y
Ind \times Year FE	Y	Y	Y	Y	Y	Y
State \times Year FE	Y	Y	Y	Y	Y	Y
Observations	79,344	79,344	79,344	79,344	79,344	79,344
Adjusted R^2	0.157	0.254	0.137	0.380	0.142	0.396
Panel B: Newly Opened Establishments						
Dep. Var.	$RShare_t^{Est,Emp}$			$RShare_t^{Est}$		
$RShare_{t-1}$	0.619*** (0.121)			0.572*** (0.114)		
$RShare_{t-1} \times Shock_t$	0.046** (0.020)			0.039** (0.020)		
Firm FE	Y			Y		
Ind \times Year FE	Y			Y		
State \times Year FE	Y			Y		
Observations	7,478			7,478		
Adjusted R^2	0.660			0.659		

Table 7
Five Portfolios Sorted on $RShare$ Within Industry

This table reports time-series average of stock returns for five portfolios sorted on share of routine-task labor ($RShare$) within industry. At the end of each June, firms in each Fama-French 17 industry are sorted into five equally weighted portfolios based on their $RShare$. *Excess Returns* are monthly returns minus the 1-month Treasury bill rate. *Excess Unlevered Returns* are monthly unlevered returns, defined as in equation (28), minus the 1-month Treasury bill rate. *DGTW-Adjusted Returns* are monthly returns adjusted following Daniel, Grinblatt, Titman, and Wermers (1997). $RShare$ is lagged by 18 months. Newey-West standard errors (Newey and West (1987)) are estimated with four lags and reported in parentheses. All returns are annualized by multiplying by 12 and are reported in percentages. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. The sample covers stock returns from July 1991 to June 2014.

	L	2	3	4	H	H-L
Panel A: Excess Returns						
$E[R] - r_f$ (%)	14.11*** (4.99)	13.17*** (4.51)	12.40*** (4.51)	12.32*** (4.41)	11.02** (4.32)	-3.10* (1.70)
σ (%)	76.77	68.57	67.54	65.48	64.13	27.62
Panel B: Excess Unlevered Returns						
$E[R^{Unlev}] - r_f$ (%)	11.64*** (4.20)	10.07*** (3.65)	9.38*** (3.50)	9.04*** (3.30)	8.32** (3.28)	-3.32** (1.55)
σ (%)	64.56	55.87	52.67	49.96	49.12	24.91
Panel C: DGTW-Adjusted Returns						
$E[R^{DGTW}]$ (%)	3.11* (1.63)	2.83** (1.32)	1.82 (1.33)	1.41 (1.42)	-0.24 (1.25)	-3.35** (1.44)
σ (%)	24.72	18.69	19.41	20.71	20.06	22.88

Table 8
CAPM Regressions

This table reports the unconditional CAPM time-series regression results in Panel A and Conditional CAPM regression results in Panel B for five portfolios sorted on share of routine-task labor (*RShare*) within industry. At the end of each June, firms in each Fama-French 17 industry are sorted into five equally weighted portfolios based on their *RShare*. *RShare* is lagged by 18 months. Newey-West standard errors are estimated with four lags for the unconditional CAPM monthly estimations and with one lag for the conditional CAPM yearly estimation, reported in parentheses. CAPM alphas are annualized by multiplying by 12 and are reported in percentages. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. The sample covers stock returns from July 1991 to June 2014.

	L	2	3	4	H	H-L
Panel A: Unconditional CAPM						
MKT β	1.26*** (0.05)	1.15*** (0.04)	1.13*** (0.06)	1.09*** (0.06)	1.03*** (0.07)	-0.23*** (0.05)
α (%)	4.08 (2.64)	4.06 (2.49)	3.40 (2.40)	3.67 (2.46)	2.79 (2.48)	-1.29 (1.70)
R^2	0.72	0.74	0.75	0.74	0.69	0.18
Panel B: Conditional CAPM						
Avg. MKT β	1.60*** (0.11)	1.45*** (0.10)	1.36*** (0.08)	1.35*** (0.10)	1.31*** (0.08)	-0.29*** (0.06)
Avg. α (%)	3.40 (4.68)	2.78 (4.20)	3.48 (3.66)	2.92 (3.42)	1.64 (3.48)	-1.76 (2.07)
Avg. R^2	0.77	0.79	0.80	0.80	0.77	0.31

Table 9

Panel Regressions of Conditional Betas and Annual Stock Returns on *RShare*

This table reports the predictability of firms' share of routine-task labor (*RShare*) on their conditional betas and annual stock returns, while controlling for known firm characteristics that predict risk. Conditional betas are calculated following [Lewellen and Nagel \(2006\)](#) for each year t . Realized annual stock returns are aggregated from July of year t to June of year $t + 1$ in percentages. *RShare* is lagged by 18 months. *Ind* indicates the Fama-French 17 industries. See the Appendix for definitions of firm characteristics. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. The sample covers stock returns from July 1991 to June 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Conditional Betas									
RShare $_{t-1}$	-0.48*** (0.09)	-0.45*** (0.09)	-0.48*** (0.09)	-0.48*** (0.09)	-0.52*** (0.09)	-0.52*** (0.09)	-0.50*** (0.09)	-0.47*** (0.09)	-0.52*** (0.09)
Cash Flow $_{t-1}$		-0.04*** (0.01)						-0.04*** (0.01)	-0.03*** (0.01)
Stock Ret $_{t-1}$			0.16*** (0.03)					0.20*** (0.03)	0.23*** (0.03)
Op.Lev $_{t-1}$				-0.01 (0.02)				-0.07*** (0.02)	-0.09*** (0.02)
Mkt.Lev $_{t-1}$					0.36*** (0.07)			0.32*** (0.08)	0.13 (0.08)
Size $_{t-1}$						-0.09*** (0.01)		-0.09*** (0.01)	-0.10*** (0.01)
B/M $_{t-1}$							0.11*** (0.03)	-0.04 (0.03)	-0.03 (0.03)
Fixed Effects	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Yr
Observations	41,080	41,080	41,080	41,080	41,080	41,080	41,080	41,080	41,080
Adjusted R^2	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.05
Panel B: Annual Stock Returns									
RShare $_{t-1}$	-5.66** (2.28)	-5.33** (2.28)	-5.83** (2.33)	-6.81*** (2.30)	-7.09*** (2.33)	-6.66*** (2.33)	-7.70*** (2.35)	-8.69*** (2.43)	-12.11*** (2.30)
Cash Flow $_{t-1}$		-0.37** (0.16)						-0.21 (0.16)	-0.24 (0.16)
Stock Ret $_{t-1}$			-4.85*** (0.72)					-3.23*** (0.71)	-3.22*** (0.69)
Op.Lev $_{t-1}$				2.71*** (0.47)				1.84*** (0.50)	0.76* (0.46)
Mkt.Lev $_{t-1}$					16.14*** (1.91)			2.76 (2.20)	1.24 (2.23)
Size $_{t-1}$						-2.55*** (0.21)		-1.18*** (0.21)	-1.24*** (0.21)
B/M $_{t-1}$							11.56*** (0.96)	9.12*** (1.13)	9.36*** (1.13)
Fixed Effects	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Yr
Observations	41,080	41,080	41,080	41,080	41,080	41,080	41,080	41,080	41,080
Adjusted R^2	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.11	0.07

Table 10
Robustness of Standard Errors for Panel Regressions

The table reports two alternative regression analyses with different assumptions for the correlation structure of the residuals from that in Table 9. Columns (1)-(4) report panel regression results with standard errors clustered by both firm and year. Conditional betas are calculated following Lewellen and Nagel (2006) for each year t . Realized annual stock returns are aggregated from July of year t to June of year $t + 1$ in percentages. $RShare$ is firms' share of routine-task labor lagged by 18 months. Columns (5) and (6) report Fama-MacBeth cross-sectional regression results using monthly stock returns, annualized by multiplying by 12, and with Newey-West standard errors estimated with four lags. All standard errors are reported in parentheses. *Ind* indicates the Fama-French 17 industries. See the Appendix for definitions of firm characteristics. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. The sample covers stock returns from July 1991 to June 2014.

Dep. Var.	Panel Regressions with Double-Clustered S.E.				Fama-MacBeth	
	Conditional Beta		Annual Stock Returns		Monthly Stock Returns	
	(1)	(2)	(3)	(4)	(5)	(6)
$RShare_{t-1}$	-0.47*** (0.09)	-0.52*** (0.09)	-8.69* (4.68)	-12.11** (4.77)	-4.83* (2.76)	-7.64*** (2.78)
Cash Flow $_{t-1}$	-0.04*** (0.01)	-0.03*** (0.01)	-0.21 (0.31)	-0.24 (0.32)	0.15 (0.32)	0.10 (0.32)
Stock Ret $_{t-1}$	0.20 (0.15)	0.23 (0.16)	-3.23 (2.78)	-3.22 (3.30)	-1.90 (1.88)	-2.06 (1.96)
Op.Lev $_{t-1}$	-0.07* (0.04)	-0.09** (0.04)	1.84* (1.03)	0.76 (1.41)	0.89 (0.57)	0.11 (0.81)
Mkt.Lev $_{t-1}$	0.32* (0.17)	0.13 (0.19)	2.76 (6.46)	1.24 (7.81)	-3.99 (4.78)	-5.05 (5.05)
Size $_{t-1}$	-0.09*** (0.03)	-0.10*** (0.03)	-1.18 (0.76)	-1.24 (0.81)	-0.50 (0.57)	-0.57 (0.60)
B/M $_{t-1}$	-0.04 (0.07)	-0.03 (0.07)	9.12*** (2.49)	9.36*** (2.58)	2.68*** (0.94)	2.31** (1.05)
Fixed Effects	Ind×Yr	Yr	Ind×Yr	Yr	Ind	-
Observations	41,080	41,080	41,080	41,080	482,149	482,149
Adj. R^2 /Avg. R^2	0.08	0.05	0.11	0.07	0.06	0.03

Table 11

Panel Regressions of Annual Stock Returns on *RShare* in Subsamples

This table shows the predictability of firms' *RShare* on annual stock returns in subsamples. Panel A reports the results in the subsamples based on whether the ratio of the firm's total number of employees identified in the OES microdata sample to the firm's number of employees in the Compustat data is above or below the median for that year. Panel B reports the results in the subsamples based on whether the firms mentioned two or fewer states in their 10-K annual report following Garcia and Norli (2012) and Tuzel and Zhang (2015). Panel C reports the results in the subsamples based on whether the firm's market capitalization is below or above the median for that year. See the Appendix for definitions of variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. The sample covers stock returns from July 1991 to June 2014 in Panel A and Panel C and from July 1994 to June 2010 in Panel B.

	(1)	(2)	(3)	(4)
Panel A: Subsample by Employment Identification Ratio				
	Below Median		Above Median	
RShare _{t-1}	-8.11*** (3.08)	-9.24*** (2.96)	-9.24** (3.84)	-16.23*** (3.57)
Firm Control	Yes	Yes	Yes	Yes
Fixed Effects	Ind×Yr	Yr	Ind×Yr	Yr
Observations	20,402	20,402	20,395	20,395
Adjusted R ²	0.12	0.09	0.11	0.07
Panel B: Subsample by Geographic Dispersion				
	Two or Fewer States in 10-K		More than Two States in 10-K	
RShare _{t-1}	-19.46** (7.99)	-22.68*** (7.33)	-9.52*** (3.13)	-12.54*** (2.99)
Firm Control	Yes	Yes	Yes	Yes
Fixed Effects	Ind×Yr	Yr	Ind×Yr	Yr
Observations	3,806	3,806	21,934	21,934
Adjusted R ²	0.08	0.08	0.12	0.07
Panel C: Subsample by Firm Size				
	Below Median		Above Median	
RShare _{t-1}	-12.77*** (3.75)	-16.50*** (3.59)	-3.33 (2.28)	-5.62** (2.18)
Firm Control	Yes	Yes	Yes	Yes
Fixed Effects	Ind×Yr	Yr	Ind×Yr	Yr
Observations	20,547	20,547	20,533	20,533
Adjusted R ²	0.10	0.07	0.19	0.11

Table 12

Time-Series of Firms' Characteristics and Risk around Recessions

Panel A presents the production characteristics of firms in the top (H) and bottom (L) quintile portfolios sorted by share of routine-task labor ($RShare$) within industry, as well as the unpaired difference in means test results between the two portfolios ($H - L$). Panel B presents the market betas of the two quintile portfolios and the long-short portfolio. In the year 2000 and 2007, firms in each Fama-French 17 industry are sorted into five equally weighted portfolios based on their $RShare$ in the previous year. The portfolio formation maintains the same for four years. $Mach/Emp$ is the ratio of machinery at cost (Compustat item FATE) to number of employees (EMP) in million dollars per employee. $Op.Lev$ is the operating leverage defined following Novy-Marx (2011). Firms are required to have $Mach/Emp$ and $Op.Lev$ available for all four years around the recessions and also have stock returns available for 48 months around the recessions (i.e., July 2000 to June 2004 and July 2007 to June 2011). $MKT \beta$ is the regression coefficient of regressing the portfolios' excess returns on the market excess returns from July of the current year to June of the following year, respectively. Standard errors are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. See the Appendix for definitions of the production characteristics.

	Portfolios Formed in Year Prior to Recession			
	$t - 1$	Recession	$t + 1$	$t + 2$
Panel A: Firm Production Characteristics				
	<i>Mach/Emp</i>			
H	0.067*** (0.004)	0.071*** (0.004)	0.077*** (0.005)	0.079*** (0.005)
L	0.080*** (0.008)	0.083*** (0.009)	0.089*** (0.009)	0.090*** (0.009)
H-L	-0.014* (0.008)	-0.012 (0.008)	-0.011 (0.009)	-0.011 (0.009)
	<i>Op.Lev</i>			
H	1.257*** (0.042)	1.295*** (0.044)	1.233*** (0.043)	1.206*** (0.043)
L	1.117*** (0.057)	1.171*** (0.056)	1.105*** (0.055)	1.079*** (0.054)
H-L	0.141** (0.071)	0.124 (0.075)	0.128* (0.074)	0.127 (0.077)
Panel B: Portfolio Risk Measure				
	<i>MKT β</i>			
H	0.709*** (0.110)	1.416*** (0.125)	1.156*** (0.105)	1.233*** (0.115)
L	0.992*** (0.158)	1.492*** (0.093)	1.354*** (0.115)	1.290*** (0.148)
H-L	-0.283** (0.115)	-0.075 (0.097)	-0.198** (0.085)	-0.057 (0.112)