Labor-Technology Substitution: Implications for Asset Pricing

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Abstract

This paper studies the asset pricing implications of a firm's opportunities to replace routine-task labor with automation. I develop a model in which firms optimally undertake this replacement when their productivity is low. Hence, firms with routine-task labor maintain a replacement option that hedges their value against unfavorable macroeconomic shocks and lowers their expected returns. Using establishment-level occupational data, I construct a measure of firms' share of routine-task labor. Compared to their industry peers, firms with a higher share of routine-task labor (i) invest more in machines and reduce more routine-task labor during economic downturns, and (ii) have lower expected returns.

JEL Classification: E22, E23, G12, J24

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Labor economists argue that in recent decades, automation tends to replace workers who perform procedural and rule-based tasks, i.e., routine tasks.[1] In addition, Jaimovich and Siu (2014) find that the disappearance of routine-task jobs tends to occur mainly during recessions and that such job disappearance accounts for almost all job loss in the three most recent recessions.[2] Connecting these findings to a firm's production, it seems that adopting machines to replace routine-task labor (*labor-technology substitution*) is an economically important decision that varies with the business cycle. Such state-contingent decisions can reflect important investment opportunities that firms encounter.

In this paper, I study whether these opportunities for labor-technology substitution are a source of macroeconomic risk that is priced in the cross-section of stock returns. Compared to growth opportunities (Berk, Green, and Naik (1999)), the opportunities for labor-technology substitution have two distinctive features in my model. First, labor-technology substitution features cost-saving rather than scale-expansion. Second, the substitution may interrupt firm production. For example, prior literature suggests that investment in adopting technologies is often accompanied by plant restructuring (Cooper and Haltiwanger (2006)), worker retraining (Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen (2016)), and organizational restructuring (Bresnahan, Brynjolfsson, and Hitt (2002)), all of which are likely to interrupt production. Given this interruption, firms optimally choose to switch technologies when their productivity is low. Hence, if the economy experiences negative productivity shocks, firms that have not yet switched technologies (due to their superior past productivity) can do so. The increase in firm value through this switching acts as a hedge against the shocks and lowers their risk premia.[3] In other words, firms with a higher share of routine-task labor have more abundant technology-switching options to hedge their value against unfavorable aggregate shocks.

To study the empirical relation between routine-task labor and risk premia, I construct a

[1] Examples of routine-task labor over the past 30 years include clerks, production line assemblers, travel agents, bank tellers, and tax preparers. Acemoglu and Autor (2011) provide an excellent review of the literature in this area. Throughout this paper, I use *machines* to refer to both equipment and software.

[2] Jaimovich and Siu (2014) show that routine-task jobs constitute 89%, 91%, and 94% of all job loss in the 1990, 2001, and 2008-2009 recessions, respectively.

[3] A 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. This restructuring resulted in the 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 this restructuring, the company's unlevered equity beta increased from 1.08 in the three years before the Great Recession (2005-2007) to 1.49 in the three years after the recession (2010-2012).

measure of a firm's share of routine-task labor (*RShare*) using new microdata from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics. The OES microdata provide employment and wages for over 800 detailed occupations in 1.2 million establishments in the U.S. over three-year cycles, covering 62% of total national employment from 1990 to 2014. Following the labor economics literature, I classify occupations into routine-task labor and non-routine-task labor.[4] I then define a firm's *RShare* as the ratio of the total wages paid to its routine-task labor relative to its total wage expense.

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 have a lower proportion of machines in their total capital than their industry peers with a low *RShare*. This relation is consistent with the model assumption that routine-task labor and machines are substitutes. High-*RShare* firms also have a higher operating cost and higher operating leverage, which is consistent with the model assumption that routine-task labor is more costly to use than machines. Finally, high-*RShare* firms have higher cash flows. This relation is consistent with the model implication that high-performing firms face a higher opportunity cost for switching technologies, thus they are more likely to retain their routine-task labor than switch to machines.

The main empirical findings in this paper are twofold. First, I find that, in response to unfavorable aggregate productivity shocks, high-*RShare* firms increase the extent of their labor-technology substitution more than low-*RShare* firms. This finding is supported by three pieces of evidence: When GDP growth is low, high-*RShare* firms (1) invest more in machines (although aggregate investment is dampened), (2) reduce more routine-task labor, and (3) reduce additionally more routine-task labor when they invest in machines, compared to their industry peers with a low *RShare*.[5] To the best of my knowledge, this is the first empirical evidence that routine-task labor is *substituted* by machines within firms during economic downturns.[6] In addition, these results are evidence that high-*RShare* firms

[4]Routine-task labor is measured based on a modified version of the methodology by Autor and Dorn (2013) to take into account the evolution of technological replacement over time. See Section 2 for details.

[5]Additional robustness checks suggest that the employment results are not driven by local labor market conditions, nor are they affected by general equilibrium effects, since accounting for wages does not affect the results.

[6]Most studies on routine-biased technological change use individual-level occupational data, such as the Decennial Census data or the Current Population Survey data. These data have limitations in linking individuals to firms. Hence, it is difficult for these studies to explore firms' employment of routine-task labor and investment in machines jointly to establish the *substitution* argument.

have more abundant technology-switching options that can be exercised during economic downturns.

Second, I find strong negative relations between firms' *RShare* and their exposure to systematic risk and expected stock returns. I use both time-invariant and time-varying market betas (Lewellen and Nagel (2006)) in the Capital Asset Pricing Model (CAPM) to proxy for firms' exposure to systematic risk. I use future stock returns to proxy for firms' expected returns. I find that sorting portfolios of firms by *RShare* within industry generates a monotonically decreasing pattern in both the market betas and future excess returns. In contrast, I find no relation between alphas and *RShare* quintiles, which indicates that excess returns are explained by market betas. The betas of the high-*RShare* quintile portfolio are more than 20% lower than those of the low-*RShare* quintile portfolio, suggesting that high-*RShare* firms are less risky. In addition, comparing the high- and low-*RShare* quintile portfolios yields a negative return spread of -3.1% per year.[7]

An alternative explanation for this low risk premia for high-*RShare* firms is that high-*RShare* firms may have lower operating leverage, since routine-task labor may be easier to adjust than non-routine-task labor or machines. Note that operating leverage can be caused not only by "limited operating flexibility," i.e., the flexibility to adjust production cost, but also by the "level of gearing," i.e., the share of production cost in total revenue (Novy-Marx (2011)). I have shown in the data that high-*RShare* firms actually have higher operating costs and higher operating leverage than low-*RShare* firms. This is consistent with my model, which focuses on the "level of gearing" channel, but it is not consistent with the alternative explanation, which focuses on the "limited operating flexibility" channel. Moreover, I show that after controlling for operating leverage, *RShare* becomes more negatively associated with expected returns.

This paper contributes to the asset pricing 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), Kogan and Papanikolaou (2014), among others). This paper shows that investment opportunities, fueled by

[7]Sorting portfolios based on *RShare* across all firms, instead of within industry, generates a return spread of more than -4.8% per year (see the Internet Appendix). The robustness of this negative relation between firms' *RShare* and their expected returns is further confirmed using panel regressions that controls for known return predictors, alternative industry classifications, and measurement errors (see Section 3).

labor-saving technologies, can also represent technology-switching options. In contrast to growth options, which increase firm output and are risky options, technology-switching options increase firm efficiency and are hedging options.[8] Thus, my model complements existing theories and improves our understanding of the links between firms' investment opportunities and stock returns.[9]

The rationale for technology-switching options to be known and priced by investors is supported by the literature on the slow adoption of technologies. A large number of studies show that technology adoption is remarkably slow. For instance, the average time length for a new technological product to diffuse from 10% to 90% (of the full adoption level) is over 10 years.[10] Indeed, firms' investment in adopting technologies can be affected by new driving factors, such as the production interruption proposed in this paper. Given that adopting new technologies accounts for a major portion of investment opportunities in recent decades (see Greenwood, Hercowitz, and Krusell (1997) and Papanikolaou (2011)), incorporating new results of technology adoption to investment-based asset pricing, such as technology-switching options, is a valuable extension.[11]

My empirical findings contribute to a growing body of literature on labor heterogeneity and the cross-section of stock returns. Eisfeldt and Papanikolaou (2013) show that firms with more organization capital have higher expected returns because key talent, who owns a firm's organization capital, can walk away in response to priced technology frontier shocks. Donangelo (2014) shows that firms in industries with mobile workers are more exposed to systematic risks, because mobile workers can walk away for outside options in bad times, making it difficult for capital owners to shift risk to employees.[12] My work differs from these studies by exploring a new aspect of labor heterogeneity for a firm, namely, the heterogeneous extent to which a firm can replace its workers with machines. Hence, my paper derives the effect of labor heterogeneity on firm risk through the channel of firms' investment opportunities,

[8] Ai and Kiku (2013) argue that growth options may also be hedging options in a general equilibrium setup.

[9] This model can also be easily extended to analyze a firm's decision on exploiting of other types of cost-reducing opportunities as long as the process hinders the firm's current production, such as outsourcing production to foreign countries, or replacing older machines with new machines.

[10] For another example, Manuelli and Seshadri (2014) show that it took about 40 years for tractors to replace horses and mules in the U.S. See David (2015) and Greenwood (1999) for reviews of this literature.

[11] Along this line, Garleanu, Panageas, and Yu (2012) show that understanding the process of technology adoption can help explain many well-documented stock return predictors.

[12] A partial list of other studies in this literature includes Gourio (2007), Chen, Kacperczyk, and Ortiz-Molina (2011), Belo, Lin, and Bazdresch (2014) Belo, Lin, Li, and Zhao (2015), and Tuzel and Zhang (2015).

while the previous studies derive the effect from employees' outside options.[13]

Finally, this paper also contributes to the labor economics literature on routine-biased technological changes (RBTC). By linking the trade-off between using routine-task labor and using machines to aggregate productivity, my theoretical and empirical results propose that RBTC is more pervasive during economic downturns. This mechanism can not only help understand the time-series patterns of RBTC but also have implications for other studies. For example, this mechanism provides a potential explanation for Jaimovich and Siu (2014)'s findings on the disappearance of routine-task jobs during the recessions. For another example, it also coincides with Hershbein and Kahn (2016), who find that firms increase demand for high-skilled non-routine-task labor but not for routine-task labor after the 2008-2009 Great Recession.

The rest of this paper is organized as follows. Section 1 develops a simple "technology-switching" model. Section 2 details my procedure for measuring firms' share of routine-task labor. Section 3 presents the empirical tests of the model's predictions. Section 4 concludes.

1. Model

In this section, I develop a simple "technology-switching" model to guide my empirical tests.

1.1. Setup

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 a firm's value is equal to the market value of its equity.

Each firm has one production project, and firms differ from each other in two aspects:

[13] In terms of empirical measures, non-routine-task labor differs from key talent since non-routine-task labor includes occupations beyond key talent. For instance, non-routine-task labor includes janitors, nurses, and fitness instructors whose tasks cannot easily be replaced by machines. See more examples of routine-task labor and non-routine-task labor in the Internet Appendix.

cash flows and type.[14] The cash flows generated by firm j at time t are given by

$$A_{jt} = e^{x_t + \epsilon_{jt}}, \tag{1}$$

where x_t is the aggregate shock that affects the cash flows of all existing firms, and ϵ_{jt} is the firm-specific shock. While the aggregate uncertainty contributes to aggregate risk premium, the firm-specific shocks contribute to firm heterogeneity in the model. All shocks follow geometric Brownian motion, i.e.,

$$\begin{aligned} dx_t &= \sigma_x dB_{xt} \\ d\epsilon_{jt} &= \sigma_\epsilon dB_{\epsilon t}, \end{aligned} \tag{2}$$

where B_{xt} and $B_{\epsilon t}$ are Wiener processes independent of each other. Hence, the dynamics of A_{jt} evolve according to

$$dA_{jt} = A_{jt}\sigma_a dB_t, \tag{3}$$

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

There are two types of firms, *automated firms* and *unautomated firms*, characterized as follows: First, following the task-based characterization of production (Acemoglu and Autor (2011)), I assume that a firm generates cash flows only when both routine tasks and non-routine tasks are performed. Second, each firm requires fixed units of non-routine-task labor such as managers and janitors to perform the non-routine tasks. Third, a firm's routine tasks can be performed by either fixed units of routine-task labor or fixed units of machines, a choice which defines the firm's type.

If the firm hires routine-task labor, it starts producing immediately. I refer to these firms as *unautomated firms*. All firms start as unautomated and can switch to *automated firms* by adopting machines to replace their routine-task labor. When doing so, an unautomated firm lays off its routine-task labor and pays I_M to buy the machines on the initiation date.

[14] I do not allow for growth options in this model by assuming that all firms are single-project firms. This assumption set the model focus to firms' decisions on reducing costs rather than expanding scales. In an extended model in the Internet Appendix, I relax this assumption by allowing for exit and entry of projects within a firm.

I assume that using machines reduces production cost by f_R compared to using routine-task labor. Specifically, let the production cost for automated firms be f per unit of time, which includes the cost of using machines, total wages paid to non-routine-task labor, and other expenses. Then, the production cost for unautomated firms is $f + f_R$ per unit of time. I assume that technology has evolved to a stage such that this replacement is profitable, that is, $I_M < \frac{f_R}{r}$.[15] For simplicity, I assume that the process of the firm-specific shock is not affected after a firm's type is switched. Finally, all machines, once they are purchased and customized to the firm's production, have zero resale value.

The key countering force that constrains the firm from adopting machines immediately is that it takes the firm T units of time to adapt the technologies embodied in the machines. The newly-automated firm does not generate any cash flows until the T periods are passed. The cost-saving benefit from the replacement and this opportunity cost (due to production interruption) constitute the trade-off that the firm faces when switching technologies.

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

$$\pi_u(t) = A_t - f - f_R, \tag{4}$$

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

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

1.2. Valuation

Following Berk, Green, and Naik (1999) and Zhang (2005), I assume that firms maximize their value by taking as given a stochastic discount factor. The stochastic discount factor evolves according to

$$\frac{d\Lambda_t}{\Lambda_t} = -r dt - \sigma_\Lambda dB_{xt}, \tag{6}$$

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

[15] Greenwood, Hercowitz, and Krusell (1997) and Papanikolaou (2011) argue that a large part of technology progress after World War II is investment-specific and can be inferred from the declines in quality-adjusted prices of new equipment.

Value of automated firms Since automated firms do not have real options, their value is simply the discounted value of their future profits. Hence, the value of an automated firm initiated at t_0 is

$$\begin{aligned} V_a(t_0;t) &= E_t \int_0^\infty \frac{\Lambda_{t+s}}{\Lambda_t} \pi_a(t_0, t+s) ds \\ &= \frac{e^{-(r+\sigma_x\sigma_\Lambda)t'}}{r+\sigma_x\sigma_\Lambda} A_t - \frac{f}{r}, \end{aligned} \tag{7}$$

where $t' = \max(t_0 + T - t, 0)$ is the time to wait (for the firm to start producing).

Value of unautomated firms The value of an unautomated firm can be divided into the value of assets in place, $V_u^{ap}(t)$, and the value of the switching option, $V_u^{so}(t)$:

$$V_u(t) = V_u^{ap}(t) + V_u^{so}(t). \tag{8}$$

The value of assets in place is simply the discounted value of future profits. Hence,

$$V_u^{ap}(t) = \frac{1}{r+\sigma_x\sigma_\Lambda} A_t - \frac{f+f_R}{r}. \tag{9}$$

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

$$V_u^{so}(t) = \text{Payoff}(t+\tau)\hat{\mathbb{E}}_t[e^{-r\tau}], \tag{10}$$

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

$$\begin{aligned} \text{Payoff}(t) &= V_a(t;t) - V_u^{ap}(t) - I_M \\ &= \frac{f_R}{r} - I_M - \frac{1-e^{-(r+\sigma_x\sigma_\Lambda)T}}{r+\sigma_x\sigma_\Lambda} A_t. \end{aligned} \tag{11}$$

Hence, the switching option can be viewed as an investment opportunity with a fixed benefit, a fixed direct cost, and a variable opportunity cost that is low if the firm is doing poorly.

Proposition 1 (Optimal exercise of the switching option): *The optimal strategy to switch from an unautomated firm to an automated firm is when the firm's cash flows, A_t, fall below*

a fixed threshold A^*, where

$$A^* = v\xi \frac{r + \sigma_x \sigma_\Lambda}{1 - e^{-(r+\sigma_x\sigma_\Lambda)T}}, \tag{12}$$

and the value of the unautomated project is

$$V_u(t) = \frac{1}{r + \sigma_x \sigma_\Lambda} A_t - \frac{f + f_R}{r} + \xi A^{*v} A_t^{-v}, \tag{13}$$

where $v > 0$ and ξ is the optimal payoff of the switching option when the option is exercised.

Appendix A.1 provides the proof. This proposition immediately leads to the following testable corollary:

Corollary 1 (Cross-section of investment and employment): *If the economy experiences a negative shock, that is, $dx_t < 0$, unautomated firms invest more in machines and lay off more routine-task labor than automated firms.*

1.3. Firm Risk

Define a firm's equity beta as the scaled covariance of the firm's value and the stochastic discount factor, and is further normalized to be 1 for revenue.[16] Let $V_a^f = \frac{f}{r}$ and $V_u^f = \frac{f+f_R}{r}$ be the capitalized value of operating costs in automated firms and unautomated firms, respectively. Let β_u^{so} be the beta of V_u^{so}. Then, $\beta_u^{so} = -\frac{(1+v)\xi A^{*v} A_t^{-v}}{V_u^{so}} < 0$.

Proposition 2 (Equity betas): *The beta of an automated firm is*

$$\beta_a = 1 + \frac{V_a^f}{V_a}, \tag{14}$$

and the beta of an unautomated firm is

$$\beta_u = 1 + \frac{V_u^f}{V_u} + \frac{V_u^{so}}{V_u} \beta_u^{so}. \tag{15}$$

Define a firm's operating leverage as $\frac{V^f}{V}$ (see Novy-Marx (2011)), we have:

Corollary 2 (Source of differences in firm risks): *The cross-sectional comparison of betas between an unautomated and an automated firm is subject to two channels through operating*

[16] That is, $\beta = -\frac{\sigma_\Lambda}{\sigma_x} \frac{\mathrm{Cov}\left[\frac{dV}{V} \frac{d\Lambda}{\Lambda}\right]}{\mathrm{Var}\left[\frac{d\Lambda}{\Lambda}\right]}$. Multiply and divide this equation by $d \log A$, we have $\beta = \frac{d \log V}{d \log A}$.

leverage and switching options:[17]

$$\beta_u - \beta_a = \underbrace{\frac{V_u^f}{V_u} - \frac{V_a^f}{V_a}}_{\textit{operating leverage channel}} + \underbrace{\frac{V_u^{so}}{V_u}\beta_u^{so}}_{\textit{switching options channel}}. \tag{16}$$

Given that $\beta_u^{so} < 0$, the effect of the switching options channel is straightforward: Unautomated firms have the switching option that hedges their value against unfavorable aggregate shocks and lowers their equity betas. Hence, controlling for operating leverage, unautomated firms are always less risky than automated firms. We will test this hypothesis in the next section.

The effect of the operating leverage channel is less clear. While it is well documented that operating leverage increases firm risk (see, for example, Novy-Marx (2011) and Donangelo (2014)), it is unclear whether unautomated firms have higher or lower operating leverage than automated firms in this model. On the one hand, we have $V_u^f > V_a^f$ because routine-task labor costs more than machines. One the other hand, unautomated firms on average have higher cash flows than automated firms due to the optimal exercise of the switching option. Specifically, unautomated firms cannot have cash flows below A^* at any time. The higher cash flows increase the value of unautomated firms and lower their operating leverage relatively to automated firms.

To assess how does the operating leverage channel contaminate the hedging effect of the switching options channel on firm risks on average, I compare betas of unautomated firms and automated firms at the portfolio level, by taking the dynamics of this model literally.

Proposition 3 (Comparison of portfolio betas): *Assume that all firms start as unautomated with the same initial level of cash flows A_0, where $A_0 > A^*$. Define $\beta_U(s)$ and $\beta_A(s)$ as the beta of the unautomated-firm portfolio and the automated-firm portfolio at time s, respectively. Then, after sufficiently long time periods t, we have:*

$$\beta_U(t) < \beta_A(t). \tag{17}$$

Intuitively, at any time, firms that remain unautomated are *survivors* with a path of cash

[17] The coexistence of the operating leverage channel and the real options channel is general in investment-based asset pricing models. These two channels oftentimes have opposing effects on firm risks (see for example Hackbarth and Johnson (2015)).

flows above A^* for all the time in the past. Due to this selection on past path, the average cash flows of unautomated firms increase over time. In contrast, the average cash flows of automated firms are bounded. Hence, as cash flows of unautomated firms increase over time relative to automated firms, the opposing effect of the operating leverage channel diminishes and the hedging effect of the switching options channel dominates the comparison of portfolio betas. I formalize these intuitions in a proof in Appendix A.2.

In summary, this simple model yields several empirical predictions: (1) if the economy experiences a negative shock, unautomated firms invest more in machines and lay off more routine-task labor than automated firms; (2) controlling for operating leverage, unautomated firms have lower equity betas than automated firms; (3) in the model dynamics, the portfolio of unautomated firms is expected to have lower betas than the portfolio of automated firms.

2. Measuring a Firm's Routine-Task Labor

2.1. Data and Methodology

My model suggests that unautomated and automated firms can be identified by the significance of routine-task labor in firms' production costs. I thus measure a firm's share of routine-task labor, *RShare*, as the ratio of the total wages paid to its routine-task labor relative to its total wage expense. In this section, I describe the data and methodology that I use to construct this measure. Specifically, 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 a firm's *RShare* following the definition above.

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. Besides 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.

Using the OES microdata, I estimate the median hourly wages for each occupation in each establishment from 1998 onwards. The OES microdata do not have wage information before 1998. Hence, for years before 1998, I estimate the hourly wages from the Census Current Population Survey Merged Outgoing Rotation Groups (CPS-MORG).[18] The total wages paid to an occupation in an establishment is simply the product of the employment and the hourly wages.

I aggregate establishments to the Compustat firms using EINs and supplement the matching by using legal names.[19] 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. Given that the OES survey covers each establishment in 3-year cycles, this methodology provides a better coverage of a firm's operation than using only firms' establishments at year t. This procedure identifies the occupation composition for an average of 3,857 Compustat firms in each year from 1990 to 2014.

I next identify occupations that can be classified as routine-task labor. 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 skill information 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.[20] I re-

[18]From the CPS-MORG, I calculate the hourly wages for 504 occupations in 13 broad industries by averaging hourly wages of individuals aged from 18 to 65 within each group, weighted by the personal earnings weights. To crosswalk a Census occupation to an OES occupation, I link Census and OES occupational codes to a finer occupational classification—the Dictionary of Occupational Titles (DOT)—and build the crosswalk if the Census occupation covers more than 50% of the DOT occupations that the OES covers. When possible, I impute the hourly wage for each occupation-industry (SIC 3-digit) 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.

[19]Some 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 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 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 an unreported analysis, I conduct a fuzzy matching via legal names, using the stata ado file "reclink" written by Michael Blasnik. The resulting measure is very close to the *RShare* measure.

[20]Specifically, abstract analytic skill is measured by mathematical skill. Abstract interactive skill is mea-

scale these skill levels to be between 1 and 10. I then take the average of the routine cognitive and routine manual skill levels as the skill level required by the occupation in performing routine tasks. Similarly, I obtain the skill level required by each occupation in performing abstract tasks. Given that the Revised Edition of the DOT is available after 1991, to avoid using lookahead 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-routine manual tasks for occupations before 1991.

I aggregate the DOT occupations to the OES occupation level. 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).[21]

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

$$RTI_k = \ln(T_k^{\text{Routine}}) - \ln(T_k^{\text{Abstract}}) - \ln(T_k^{\text{Manual}}), \tag{18}$$

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 in the previous two years to represent the current year's labor force.[22] I then sort all workers in current year's labor force based on 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.[23] By classifying routine-task labor each year, this measure of routine-task labor accounts for technological evolution. In particular, it accounts for the fact that certain occupations that are not substitutable by machines in previous years become

sured 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.

[21] 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 are 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.

[22] This approach is suggested by the OES program and is also used by the OES to produce statistics for public use, see http://www.bls.gov/oes/tables.htm.

[23] In the Internet Appendix, I classify routine-task labor at alternative cutoffs, such as the top quartile of the RTI score distribution, and find my results robust to alternative measures of routine-task labor.

substitutable because their RTI rankings increase over time.

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

$$RShare_{j,t} = \sum_k \mathbb{1}\left[RTI_k > RTI_t^{P80}\right] \times \frac{emp_{j,k,t} \times wage_{j,k,t}}{\sum_k emp_{j,k,t} \times wage_{j,k,t}}, \tag{19}$$

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 year 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 year t, respectively.

I finalize my sample selection by imposing additional requirements based on firms' accounting and stock return information. Appendix B 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.

2.2. Validation

To evaluate my measure of routine-task labor, I examine the characteristics of occupations that are classified as routine-task labor. Panel A of Table 1 shows that routine-task labor has a significant presence in all major occupation groups except for management. Notably, 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.

I also examine whether routine-task labor proxies for jobs that can be outsourced. 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 for this claim. In particular, Panel B of Table 1 shows that offshorability has a small negative correlation with both the routine-task labor dummy and the RTI score, indicating that offshorability and routine capture different aspects of an occupation.

Labor economic literature shows that jobs that are susceptible to technological substitution tend to be those of middle-class workers with moderate skills. Consistent with the literature, I find a moderate negative correlation of the routine measures and occupations' median wages and skills. In the Internet Appendix, I provide examples routine-task labor

and non-routine-task labor to strengthen this point.[24]

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 of occupations, suggesting that unions are unlikely to be a major factor in hiring routine- versus non-routine-task labor. In summary, the above results suggest that my measure of routine-task labor is consistent with the literature's characterization of routine-task jobs.

Finally, Jaimovich and Siu (2014) show that routine-task jobs, defined based on three major occupation groups, disappear in the past three recessions but not in expansions. I thus examine the employment of routine-task employment, defined using my proposed methodology, over the business cycle. Such dynamics can also provide the pro forma evidence on firms' labor-technology substitution under different economic conditions.

Given that the OES data underwent a major change in occupation classification in 1999, they are not suitable for time-series analysis that requires tracking a given set of occupations over time. I thus use the CPS monthly data which have a time-series consistent measure of occupation, *occ*1990, from the Integrated Public Use Microdata Series database. I classify occupations based on the distribution of RTI scores using the 1990 Census data. Specifically, I classify each occupation in the 1990 Census as *routine-task labor (1990)* or *non-routine-task labor (1990)* using the methodology described in Section 2.1. I then track the employment of these two groups of occupations from January 1988 to December 2015.

Figure 1 plots employment dynamics for routine-task labor (1990) and non-routine-task labor (1990). Consistent with the literature, we see that the employment of routine-task labor (1990) declines over time, while the employment of non-routine-task labor (1990) rises. More importantly, we see that while the employment of routine-task labor (1990) declines during recessions, it does not tend to bounce back during the recovery periods as the employment of non-routine-task labor (1990) does. These observations support my model's prediction that firms replace routine-task labor with machines in bad times, which I will test in depth in the next section.

[TABLE 1 ABOUT HERE]

[24]It is important to conceptually disentangle routine-task labor form unskilled workers, and non-routine-task labor from skilled workers. In particular, note that non-routine-task labor also includes some unskilled workers such as manual workers. This distinction helps to distinguish my study from Eisfeldt and Papanikolaou (2013) who find that key talents (skilled workers) impose additional risk on firms.

[FIGURE 1 ABOUT HERE]

3. Empirical Evidence

My model predicts that in response to unfavorable aggregate shocks, firms with a high share of routine-task labor invest more in machines and reduce more of their routine-task labor than firms with a low share of routine-task labor. Hence, firms with a higher share of routine-task labor have more abundant hedging options which lower their exposure to systematic risk. In this section, I empirically test these predictions.

3.1. RShare and Firm Characteristics

Panel A of Table 2 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, cross-sectional variation in *RShare* is not likely to be concentrated in 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, while my model keeps this intensity fixed and focuses on the factor inputs in performing the routine tasks.

Panel B of Table 2 shows that high-*RShare* firms have lower stocks of machinery and equipment relative to their physical capital and also relative to their structural capital (e.g., buildings and land), indicating that high-*RShare* firms replace their routine-task labor with machines to a lesser extent than low-*RShare* firms. 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.

To examine the relation of firms' *RShare* and their operating leverage, I construct a

measure of firms' operating leverage that closely follows the model definition. In the model, a firm's operating leverage is the firm's capitalized production cost divided by its value. I thus measure firms' operating leverage as the sum of the cost of goods sold (COGS) and the selling, general & administrative expense (SG&A) divided by firm size. Carlson, Fisher, and Giammarino (2004) argue that in theory a firm's book-to-market ratio proxies for its operating leverage. Hence, I calculate firms' book-to-market ratio as an alternative proxy for their operating leverage. In addition, I measure a firm's operating cost as the sum of COGS and SG&A normalized by its total assets.[25] I find that high-*RShare* firms have higher operating cost, higher operating leverage, and also higher book-to-market ratio than low-*RShare* firms. These results suggest that the operating cost channel dominates the cash flows channel in determining the operating leverage for high-*RShare* and low-*RShare* firms.

I further examine the relation of *RShare* and growth opportunities and financial leverage, which are not captured in my model. Carlson, Fisher, and Giammarino (2004) suggest that a firm's growth opportunities can be proxied by its size. Hence, I examine firm size in the above five portfolios. I do not find a relation between firms' *RShare* and their size. This evidence suggests that *RShare* is not likely to be correlated with firms' growth opportunities. Interestingly, I find that firms with a high *RShare* have slightly higher financial leverage than firms with a low *RShare*.

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 2 shows that, on average, 24% to 40% of firms will opt out of their current quintile portfolio in the next year, suggesting that *RShare* is a dynamic firm characteristic.[26]

[TABLE 2 ABOUT HERE]

[25] Novy-Marx (2011) constructs a measure of firms' operating leverage following the same approach to identify the impact of operating leverage that is not captured by book-to-market ratio.

[26] To rule out the possibility that firms' year-over-year changes across *RShare* portfolios are caused by changes in data collection methods, I exclude year 1995 and year 1998 when calculating the transition probabilities, because the OES program changed survey design from 1995 to 1996 and changed occupation classification from 1998 to 1999.

3.2. 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*.

3.2.1. Investment in Machines and Aggregate Shocks

Here, I show that high-*RShare* firms invest more in machines than low-*RShare* firms in the face of unfavorable aggregate productivity shocks. Investment in machines is measured by real growth rate of machinery and equipment at cost (Compustat item FATE). The advantage of using the "at cost" measure is that it is before amortization and depreciation. Hence, year-over-year changes in this variable indicate better of the firms' gross investment in machines. I use the growth rate of real GDP value-added as a proxy for aggregate shocks.[27] Finally, I run the following panel regression:

$$I^M_{f,t} = b_0 + b_1 RShare_{f,t-1} \times Shock_t + b_2 RShare_{f,t-1} + cX_{f,t-1} + F_f + F_{Ind\times Year} + \epsilon_{ft}, \quad (20)$$

where $I^M_{f,t}$ 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 total assets), and F_f and $F_{Ind\times Year}$ denote firm and industry-year fixed effects, respectively.[28] I standardize all variables so that their means are 0 and their standard deviations are 1 in order to compare the main results with placebo test results which I will discuss later.

The first two columns of Table 3 report results without and with controls for firm characteristics. The point estimate for b_1 is negative and statistically significant, implying that high-*RShare* firms change invest in machines more positively than low-*RShare* firms in bad times. For a firm with *RShare* one-standard-deviation higher than its industry peers, a

[27] Alternatively, 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.

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

one-standard-deviation drop in real GDP growth (1.7%) increases the spread of machinery investment rate by 0.37% between the firm and its industry peers. In the Internet Appendix, I use the past two recessions as proxies for unfavorable aggregate shocks. In this case, I find that the spread of machinery investment rate between the high-*RShare* firm and its industry peers increases by 1.13% after the recessions.[29] Compared to the sample mean of machinery investment rate, 9.46%, these spreads suggest a fairly moderate effect of unfavorable aggregate shocks on accelerating labor-technology substitution on the investment side.

One potential concern is that the previous findings may be driven by that high-*RShare* firms face less procyclical growth opportunities. If this is the case, we expect that high-*RShare* firms have less procyclical investment in other capital as well. This is because, in general, when firms grow, they not only invest in machines but also are likely to invest in other capital such as structures. I thus conduct a placebo test in which I run the same panel regression but examine investment in capital other than machines.[30] Columns (3) and (4) of Table 3 report statistically and economically insignificant point estimates of b_1. Hence, cyclical growth opportunities do not seem to drive the results.

[TABLE 3 ABOUT HERE]

3.2.2. Routine-Task Employment and Aggregate Shocks

Here, I show that high-*RShare* firms reduce their routine-task labor disproportionately more than low-*RShare* firms in the face of unfavorable aggregate shocks. Measuring changes in routine-task labor at the firm level is challenging in the OES data.

Given that the OES survey covers each establishment in at most every three years, year-over-year changes in routine-task employment at the firm level is difficult to construct.[31] To overcome this limitation, I conduct the analysis at the establishment level. Another advantage of the establishment-level analysis is that we can add state-year fixed effects to control for time-varying local labor market conditions, such as state labor laws (e.g., wrongful-discharge

[29] I choose to use real GDP growth rather than recession events in the main analysis in order to also include the effects of small productivity shocks.

[30] Other capital is measured as the difference between property, plant, and equipment at cost (Compustat item PPEGT) and machinery and equipment at cost (FATE).

[31] Note that I measure a firm's routine-task labor based on its observed establishments in both the current year and over the prior two years. Hence, the year-over-year changes in a firm's routine-task labor captures the hiring and firing of routine-task labor in one-third of its establishments on average.

laws and right-to-work laws) or fluctuations in local wages (see Tuzel and Zhang (2015)). To ensure that the changes in establishments' routine-task employment is not due to change in the nature of the business, I exclude all establishments that change detailed industry classification code, i.e., SIC 4-digit or NAICS 6-digit, over the three-year survey cycles.

I construct three proxies for establishments' 3-year change in routine-task employment. The first measure is the growth rate of establishments' routine-task employment from three years before to the current year.[32] The second measure is the change in establishments' *RShare* constructed based on employment in each occupation instead of the total wage expense following equation (19). The third measure is the change in establishments' (total-wage-based) *RShare*. In constructing each of these three measures, routine-task labor is defined as of three years before so that the measures are not contaminated by reclassifying routine-task labor year-over-year. 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 4 reports the results of the following panel regression:

$$\begin{aligned} Chg^{Routine}_{e,f,t-3,t} = b_0 + b_1 RShare_{f,t-3} \times Shock_{t-3,t} + b_2 RShare_{f,t-3} \\ + F_f + F_{Ind\times Year} + F_{State\times Year} + \epsilon_{e,f,t}, \end{aligned} \tag{21}$$

where $Chg^{Routine}_{e,f,t-3,t}$ is one of the three proxies for the change in routine-task employment in firm f's establishment e from year $t-3$ to year t, $RShare_{f,t-3}$ is firm f'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. All variables are standardized for easier interpretation.

In column (1) of Panel A in Table 4, 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. For a firm with *RShare* one-standard-deviation higher than its industry peers, a one-standard-deviation drop in 3-year real GDP growth (3.91%) reduces the firms' routine-task employment by additionally 2.74% compared to its industry peers in a three-

[32] I measure the growth rate using the three year differences in routine-task employment divided by the average of routine-task employment three years before and in the current year. Davis, Haltiwanger, Handley, Jarmin, Lerner, and Miranda (2014) emphasize that "this measure has become standard in analyzing establishment and firm dynamics, because it shares some useful properties of log differences while also accommodating entry and exit." Using alternative measures leads to similar results but smaller sample size, because establishments may not have routine-task labor three years before.

year horizon, a moderate effect given that the total proportion of routine-task labor in a year is 20% by construction. Columns (2) further shows that reduction in routine-task labor during bad times is disproportionately higher in establishments from high-*RShare* firms than low-*RShare* firms. Hence, high-*RShare* firms respond to unfavorable aggregate shocks by undertaking a change in their production structure which brings their *RShare* closer to that of the low-*RShare* firms.[33]

I further address the concern that the above results could be driven by the extra stickiness of wages for routine-task labor relative to wages of non-routine-task labor. In Columns (3) and (4), I examine changes in establishments' employment-based *RShare* and total-wage-based *RShare*. If differential wage stickiness is the main driving force, firms would adjust wages for non-routine-task labor instead of altering the employment. Hence, predictions on changes in employment-based *RShare* and total-wage-based *RShare* should be very different. The comparison in Column (3) and (4) shows strikingly similar results, suggesting that heterogeneous wage stickiness is not a driving force.

3.2.3. Labor-Technology Substitution and Aggregate Shocks

One caveat of testing firms' investment and employment policies separately is that the findings may be driven by different subsets of firms. In other words, in response to unfavorable aggregate shocks, some high-*RShare* firms invest more in machines, and other high-*RShare* firms reduce more routine-task labor. But these two sets of high-*RShare* firms do not overlap. Hence, the results that we see in the previous discussion may not be sufficient to show that high-*RShare* firms are *substituting* their routine-task labor with machines. In order to show the substitution behavior, I examine the response of the correlation of firms' machinery investment and routine-task employment to aggregate shocks for high-*RShare* firms and low-

[33] It is possible that different establishments within a firm may have different *RShare*. To check whether firms are indeed laying off their routine-task labor in their high-*RShare* establishments, I report tests using the establishment's *RShare* rather than the firm's *RShare* in the Internet Appendix. I find that high-*RShare* establishments respond to unfavorable aggregate shocks by reducing more routine-task labor and lowering their *RShare*.

RShare firms. Specifically, I run the following panel regression:

$$
\begin{aligned}
Chg^{Routine}_{e,f,t-3,t} = b_0 &+ b_1 RShare_{f,t-3} \times Shock_{t-3,t} \times I^M_{f,t-3,t} \\
&+ b_2 RShare_{f,t-3} \times Shock_{t-3,t} \\
&+ b_3 RShare_{f,t-3} \times I^M_{f,t-3,t} \\
&+ b_4 Shock_{t-3,t} \times I^M_{f,t-3,t} \\
&+ b_5 I^M_{f,t-3,t} + b_6 RShare_{f,t-3} \\
&+ F_f + F_{Ind \times Year} + F_{State \times Year} + \epsilon_{e,f,t},
\end{aligned} \tag{22}
$$

where $I^M_{t-3,t}$ is firm f's 3-year real investment rate in machines. I interpret coefficient b_1 as the marginal effect of a one standard deviation decrease in real GDP growth on the gap between high-*RShare* and low-*RShare* firms in terms of the correlation between machinery investment and routine-task employment. Hence, in response to unfavorable aggregate shocks, if high-*RShare* firms indeed substitute their routine-task labor with machines more than low-*RShare* firms, the correlation between machinery investment and routine-task employment should be more negative (or less positive) than low-*RShare* firms, predicting that b_1 should be positive.

The first two columns in Panel B of Table 4 show that the point estimate of b_1 is positive and significant for the two choices of routine-task employment measure. As a placebo test, I inspect the correlation between investment in other capital and routine-task employment, and I do not find that this correlation in high-*RShare* and low-*RShare* firms responds to aggregate shocks differently, as shown in columns (3) and (4).

In summary, the findings on investment in machines and employment of routine-task labor show two opposite responses of high-*RShare* firms to unfavorable aggregate shocks compared to low-*RShare* firms. The results on the correlation between machinery investment and routine-task employment show that these two opposite responses jointly constitute an additional labor-technology substitution for high-*RShare* firms than low *RShare* firms in bad times. Together, these results support the model's core mechanism that high-*RShare* firms have more switching options to replace their routine-task labor with machines in the face of unfavorable aggregate shocks.

[TABLE 4 ABOUT HERE]

3.2.4. Driving Factors for the Substitution

My model suggests that the main driving factor for firms to replace routine-task labor with machines in bad times is the opportunity cost due to the interruption to production. Here, I inspect other potential driving factors that may explain this finding. Specifically, if routine-task workers are less willing to accept flexible wages than non-routine-task workers, or if firms expect the price of machines to drop significantly in bad times, then firms will be more likely to undertake the replacement in bad times.

The previous analyses show that the sticky-wage channel does not seem be a main driving factor, since accounting for wages does not affect firms' employment decisions on routine-task labor (see Section 3.2.2). Nevertheless, to see the wage dynamics more explicitly, in Panel A of Figure 2, I plot the average hourly wages of routine-task labor and non-routine-task labor from 1988 to 2015 using the sample of the CPS-MORG.[34] I classify each occupation in the CPS-MORG into *routine-task labor (1990)* or *non-routine-task labor (1990)* based on the RTI distribution of the 1990 Census. I then track the hourly wages of the two groups over time. The hourly wages are logged and then detrended using the Hodrick-Prescott filter (Hodrick and Prescott (1997)) to obtain their cyclical components.

Two observations stand out: First, the hourly wages of routine-task labor (1990) and non-routine-task labor (1990) behave similarly in recessions, and they are highly correlated in general, with a correlation of 0.86. Second, neither of the two series of hourly wages has much cyclical property. If any, hourly wages of routine-task labor (1990) is more cyclical than hourly wages of non-routine-task labor (1990), with the correlations to GDP equal to 0.28 and 0.06, respectively. Hence, wages of routine-task labor do not seem to be more sticky than wages of non-routine-task labor.

Inspecting the dynamics of machine prices shows that the countercyclical-machine-price channel does not seem to hold in the data either. Panel B of Figure 2 plots the quality-adjusted price of equipment and software from 1988 to 2012. This price series is aggregated from the prices of 22 groups of durable equipment and is used in earlier studies as bases for measuring investment-specific technology shocks (see, for example, Cummins and Violante (2002) and Kogan and Papanikolaou (2014)). From the plot, we see that the detrended price

[34]The CPS data are superior in showing time-series changes for occupations than the OES data because the CPS data have a time-series consistent occupation code, *occ1990*, which is provided by the Integrated Public Use Microdata Series (IPUMS).

of machines drops in the 2001 recession but goes up in the 1990 recession and in the 2008-2009 Great Recession. The correlation of machine price and GDP is -0.46, indicating that machines do not necessarily become cheaper in bad times.[35]

In summary, the pro forma evidence shows that cyclical movements of wages and machine prices do not seem to offer plausible incentive for firms to undertake labor-technology substitution in bad times.

[FIGURE 2 ABOUT HERE]

3.3. Asset Prices

My model suggests that switching options reduce firms' exposure to systematic risk. Through this channel, firms with a high *RShare* have lower expected returns than firms with a low *RShare*. Yet, high-*RShare* firms may have higher operating leverage which mitigates the effect of switching options. Therefore, tests that control for operating leverage would increase the magnitude of the negative spread in expected returns between high-*RShare* firms and low-*RShare* firms. I test these predictions in this section, starting with merging firms' monthly stock returns from the CRSP database to their *RShare*. Appendix B provides the sample selection details.

3.3.1. Portfolio Analysis

I explore the relation of firms' share of routine-task labor and their 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 *RShare*.[36] *RShare* by construction increases from 0.02 for the lowest quintile portfolio to 0.39 for the highest quintile portfolio (see Panel B of Table 2). In the first panel of Table 5, I find that excess

[35] This price series does not include prices of used equipment, which may drop during economic downturns. Eisfeldt and Rampini (2006) show that capital reallocation between firms is highly procyclical, suggesting that reduction in prices of used equipment in bad times, if any, is not driving firms' technology adoption. In addition, used equipment may embody less new technologies (Papanikolaou (2011)).

[36] I focus on equally-weighted portfolios instead of value-weighted portfolios to mitigate the influence of measurement error in *RShare* for large firms. See Section 3.3.5 for details about the analysis on measurement error. In the Internet Appendix, I find a strong negative relation between *RShare* and future returns using value-weighted portfolio sorting among small firms, but no significant results among large firms. I also strong negative relation between *RShare* and market betas among all firms, small firms, and large firms.

returns monotonically decrease from 14.11% for the lowest *RShare* quintile to 11.02% for the highest *RShare* quintile, yielding an average of −3.1% return spread per year, which is statistically significant. This return spread is in the order of magnitude of the size and value premia. For instance, the average small-minus-big size factor and the high-minus-low value factor (Fama and French (1993)) reported on Kenneth French's website are 2.7% and 3.8% per year, respectively, during this period.

I next check the robustness of the above results to financial leverage. 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 expected returns. To address this concern, I first show that low-*RShare* firms, on average, do not have higher financial leverage than high-*RShare* firms (see Panel B of Table 2). To further address time-varying financial leverage for low-*RShare* and high-*RShare* firms, I calculate firms' unlevered stock returns following Liu, Whited, and Zhang (2009), and conduct the portfolio analysis using the excess unlevered returns. The unlevered stock returns are calculated as follows:

$$R^{Unlev}_{f,m,y} = (1 - w_{f,y-1})\, R^{Raw}_{f,m,y} + w_{f,y-1} R^{Bond}_{f,m,y} \left(1 - Tax_y\right), \tag{23}$$

where $R^{Raw}_{f,m,y}$ is the monthly stock return of firm f in month m of year y, $R^{Bond}_{f,m,y}$ is the monthly bond return of firm f in month m of year y, Tax_y is the statutory corporate income tax rate at year y, and $w_{f,y-1}$ is the market leverage ratio for firm f at the end of year $y-1$.[37]

The second panel of Table 5 reports the results of excess unlevered returns for firms in five *RShare* portfolios sorted within industry. Similar to the results based on excess returns, the excess unlevered returns monotonically decrease from the portfolio with the highest *RShare* to the portfolio with the lowest *RShare*. The spread between portfolios with the highest and the lowest *RShare* is negative and significant, which is also similar to the results based on excess returns. These findings suggest that financial leverage is not driving the portfolio results.

As an additional robustness check, I examine stock returns adjusted for firm charac-

[37] Data on firm-level bond returns are rather limited. Liu, Whited, and Zhang (2009) use a method to impute corporate bond returns based on the average bond returns of firms in each credit rating category. I adopt the same method by using the Barclays US aggregate monthly bond return series from the Morningstar database for five credit rating categories: Aaa, Aa, A, Baa, and high yield. See Liu, Whited, and Zhang (2009) for details on the imputation method.

teristics to disentangle the return predictability of *RShare* with well-known cross-sectional return predictors. I follow Daniel, Grinblatt, Titman, and Wermers (1997)(DGTW) and construct the DGTW-adjusted returns by taking the difference between a stock's 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 ratio (Wermers (2004)), and momentum. Each stock is then assigned to a benchmark portfolio based on the stock's size, book-to-market ratio, and previous 12-month return. The third panel of Table 5 shows a -3.35% annual spread in the adjusted-returns between portfolios with the highest and the lowest *RShare*, indicating that standard stock characteristics cannot explain the low risk premium for high-*RShare* firms.

[TABLE 5 ABOUT HERE]

3.3.2. CAPM Betas

I explore the relation of firms' *RShare* and their exposure to systematic risk, proxied by market betas under the unconditional and the conditional CAPM frameworks. The estimation under the unconditional CAPM assumes that betas are constant over time, while the estimation of the conditional CAPM relaxes this assumption. I estimate market betas under conditional CAPM for the five portfolios described above following a methodology described in Lewellen and Nagel (2006) using monthly returns in yearly windows.

Table 6 shows that market betas estimated under both the unconditional and the conditional CAPM decrease monotonically with *RShare*. A portfolio that longs stocks in the highest *RShare* quintile and shorts stocks in lowest *RShare* quintile has an unconditional market beta of -0.23 and a conditional market beta of -0.29, both of which are highly significant. I do not find significant alphas for the long-short portfolio under either the unconditional or the conditional CAPM, indicating that the excess returns of the long-short portfolio are explained by market betas.[38]

[TABLE 6 ABOUT HERE]

[38] In the Internet Appendix, I decompose the market betas for each portfolio into cash-flow betas and discount-rate betas following Campbell and Vuolteenaho (2004). I find that cash-flow beta, which captures the exposure to the component of market risk that is highly priced, accounts for more than half of the market beta for the long-short portfolio.

3.3.3. Panel Regressions

I explore the relation of firms' *RShare* and their expected returns and systematic risk conditional on other firm characteristics, most prominently firms' operating leverage. The model predicts that by controlling for firms' operating leverage, the effect of the switching options channel will not be offset by the opposing operating leverage channel. Hence, the extent to which firms' *RShare* negatively relates to their expected returns and systematic risk should increase when operating leverage is controlled. To test this prediction, I run panel regressions as follows:

$$\begin{aligned} R_{f,t} - RF_t &= b_0 + b_1 RShare_{f,t-1} + b_2 Char_{f,t-1} + F_{Ind\times Year} + \epsilon_{f,t} \\ \beta_{f,t}^{Cond} &= b_0 + b_1 RShare_{f,t-1} + b_2 Char_{f,t-1} + F_{Ind\times Year} + \epsilon_{f,t}, \end{aligned} \tag{24}$$

where $R_{f,t} - RF_t$ is the annual excess return of firm f in year t, $\beta_{f,t}^{Cond}$ is the conditional beta of firm f in year t constructed following Lewellen and Nagel (2006), $RShare_{f,t-1}$ 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 $F_{Ind\times Year}$ denotes the industry-year fixed effects.[39]

Table 7 reports the results. Two observations stand out. First, *RShare* persistently and negatively predicts future annual excess returns (in Panel A) and conditional betas (in Panel B) with and without controlling for operating leverage, book-to-market ratio, operating cost, cash flows, size, market leverage, and lagged stock returns. A one standard deviation decrease in RShare (16% in Table 2) increases a firm's expected return by 0.85%-1.3% per year.

Second, consistent with the model prediction, *RShare* relates to future annual returns and conditional betas to a greater extent when operating leverage is controlled. In particular, in the return regressions in Panel A, the economic magnitude of the coefficient for *RShare* increases dramatically from -5.66 in the specification without firm control to -8.31 in the specification with control of operating leverage. A similar increase in economic magnitude of the coefficient for *RShare* is observed when using book-to-market ratio as an alternative proxy for operating leverage, and also observed when running regressions based on the conditional beta in Panel B.

[39] To construct a conditional beta for each firm, I regress the firm's monthly excess returns on the excess returns of the market portfolio and the lagged market portfolio in yearly windows. The firm's conditional beta in a year is the sum of the coefficients for the contemporaneous and lagged excess market returns.

[TABLE 7 ABOUT HERE]

3.3.4. Industry Classifications

In Panel A of Table 8, I examine the robustness of the panel regression results using alternative industry classifications. The main purpose for controlling for industries in the empirical analysis is to enhance the link between the empirical measure of *RShare* and the model's interpretation of *RShare* in the cross-section of firms. Specifically, in the model, firms remain unautomated (i.e., having high-*RShare*) because they endogenously choose to wait for switching later. In practice, firms across different industries may have high or low *RShare* due to the nature of the production function of their respective industries. For instance, the manufacturing industry in general has a higher need for inputs in routine tasks than the information technology (IT) industry, which relies more heavily on intellectual inputs. Hence, a higher *RShare* for a manufacturing firm relative to an IT firm does not mean that the manufacturing firm has an opportunity to narrow the gap, unless the manufacturing firm completely switches industry, which is beyond the scope if this paper.

Choosing the precise level of detail in industry classification requires careful consideration. Specifically, the highly detailed industry classification may capture heterogeneity in industries' use of technology in performing similar tasks, e.g., skilled nursing care facilities (SIC code 8051) may arguably use a better technology than intermediate care facilities (SIC code 8052). Moreover, a firm may conduct business in multiple industries when the industry classification is too detailed. For this reason, I use the Fama-French 17 industry classification in the baseline analysis to separate firms in terms of their need for routine-task inputs and non-routine-task inputs. I examine alternative industry classifications that are finer or coarser than the industry classification used in the baseline analysis. For finer industry classifications, I examine the Fama-French 49 industry classification, SIC 2-digit classification, and the 10K-based industry classifications introduced by Hoberg and Phillips (2010) with 50 and 100 industry categories. For coarser industry classifications, I examine SIC 1-digit classification and no industry control at all.

The results in Panel A of Table 8 shows that *RShare* persistently and negatively predicts future excess returns, indicating that the results are robust to industry classifications. Meanwhile, the coefficient for *RShare* increases in magnitude when the industry classification

becomes coarser. The coefficient for *RShare* in the specification with SIC 1-digit industry classification and without industry control is -11.93 and -11.67, respectively, which are significantly greater in terms of economic magnitude than the coefficient in the baseline analysis, -8.35. In this sense, my results using within-industry specification can be viewed as a conservative estimate of the relation between *RShare* and firms' expected returns.

In Panel B of Table 8, I report the panel regression results within each industry sector, defined based on the SIC 1-digit industry classification.[40] Autor, Levy, and Murnane (2003) show that labor-technology substitution is more active in manufacturing sector than in non-manufacturing sector. Hence, one would expect the hedging effect of having routine-task labor is more pronounced among firms in manufacturing sector than in other sectors. The results support this conjecture by showing that *RShare* is strongly and negatively related to expected returns in manufacturing sector. The coefficient of *RShare* estimated within manufacturing sector is -13.45, ranked second in terms of economic magnitude following the coefficient estimated within wholesale sector. The coefficient of *RShare* estimated within manufacturing sector also has the highest statistical significance among all the estimated coefficients of *RShare*, although the manufacturing sector has the largest sample size and hence more power for the test.

[TABLE 8 ABOUT HERE]

3.3.5. 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 across states. The EIN in a firm's annual reports is usually the EIN of the firm's headquarters. Hence, my *RShare* measure is likely to capture the labor composition for establishments in the state where the firm's headquarters are located. It is not obvious to see whether measurement error in *RShare* due to this reason would create a biased estimation of *RShare*'s stock return predictability. However, measurement error, if it exists, is likely to attenuate the significance

[40] Results for agriculture sector is not reported due to confidentiality concerns caused by small sample size.

of my estimation. I confirm these conjectures using subsample analyses.

In Panel A of Table 9, 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 above 10%. In the other subsample, the ratio is below 10%. A priori, the latter subsample may contain a high measurement error in *RShare* given the low coverage ratio. I find consistent results with this prior: The coefficient of *RShare* is -9.63 in the subsample with a high coverage ratio, and -6.50 in the subsample with a low coverage ratio. Surprisingly, the coefficient is still statistically significant in the subsample with a low coverage ratio.

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' operations across states. Garcia and Norli (2012) define a firm as geographically focused if few state names are mentioned in the firm's 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 data from ReferenceUSA. They find that small firms are much more geographically focused. Hence, I further divide the full 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 -12.57 for small firms and -3.18 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 empirical relation of *RShare* and expected returns is driven mostly by small firms.

[TABLE 9 ABOUT HERE]

3.3.6. Double Sorting

In Table 10, I perform conditional double sorts to allow for non-parametric association between firm characteristics and returns. Specifically, I first sort firms in each industry into three bins based on a firm characteristic. Within each bin, I further sort firms into five equally-weighted portfolios based their *RShare*, resulting in fifteen portfolios in total. For each category of *RShare* (i.e., L, 2, 3, 4, H), I report the the average excess returns across the sorts of the firm characteristic in Table 10.

Columns (2) and (3) report the return spreads between high-*RShare* and low-*RShare* firms as large as -3.94% and -3.85% per year when firms' operating leverage and book-to-market ratio (which serves as an additional proxy for operating leverage) are controlled, respectively. The larger economic magnitude of these spreads compared to the spread based on the unconditional sorting, -3.10%, support the model prediction that controlling for operating leverage enhances the negative relation between *RShare* and expected returns. Columns (4) to (8) further show that the relation between *RShare* and expected returns are robust after controlling non-parametrically for firms' operating cost, cash flows, size, market leverage, and lagged stock returns.

[TABLE 10 ABOUT HERE]

3.3.7. Exercise of Switching Options 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 underlying production structure and market betas.

I confirm this prediction in Panel A of Table 11. Using the 2001 and the 2008-2009 recessions, I track the two groups of firms that have a high and a low *RShare* for four years, starting in the year prior to each recession. Specifically, I sort firms in each of the Fama-French 17 industries into five portfolios based on their *RShare* in the year prior to

each recession (i.e., in 2000 or 2007), and I hold the portfolio formation constant over the observation period. For each portfolio, I track the average ratio of machines to employment, the average operating cost, and the market beta. Firms are required to have non-missing information for the inspected variables over all four years. I calculate the market betas for each portfolio-year using monthly returns of the portfolio within the year, and I adjust the market betas for non-synchronous trading (Dimson (1979)).

Panel A shows that the difference between the machine-to-employment ratio of high-*RShare* firms and low-*RShare* firms narrows from 14 thousand dollars per worker in the years before the recessions to 11 thousand dollars per worker in the third years after recessions, and the difference becomes statistically insignificant. In addition, the gap in operating leverage between high-*RShare* and low-*RShare* firms narrows by more than 10% and becomes statistically insignificant. These results suggest that during recessions, high-*RShare* firms undertake more dramatic measures in adopting labor-saving technology to lower their production cost than low-*RShare*.

As a result, the market betas for high-*RShare* and low-*RShare* firms are much closer 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.

To address the concern that the patterns observed above are driven by a time-series trend instead of being recession-specific, I run a simple falsification test by using expansions rather than recessions. I explore the expansions in the 1990s and early 2000s by defining the year 1997 and 2004 as the years for expansion events. Panel B of Table 11 shows that going through expansions, the gap between high-*RShare* and low-*RShare* firms in terms of either machine-to-employment ratio or operating cost remains unchanged, if not widened. Moreover, the market betas of the high-*RShare* portfolio and the low-*RShare* portfolio also remain different from each other over the years. Comparing the results in the falsification test and the main test using recession events, I conclude that the findings in the main test are not likely to be driven by a time-series trend.[41]

[41] An alternative explanation is that firms' adoption of machines during the last two recessions is driven by federal investment incentives. These incentives provide tax deductions for investments in qualified capital during the recessions, which can potentially amplify the effect of my mechanism. Hassett and Hubbard (2002) survey the literature on tax incentives and show that firms' response to the incentives is very limited. Zwick and Mahon (2016) examine the tax incentives in the last two recessions and show that these incentives are most effective for small businesses but merely for the Compustat firms. In addition, the investment incentives

[TABLE 11 ABOUT HERE]

4. Conclusion

Technology changes the way our economy produces. With the arrival of new technologies, some human skills are upvalued by better tools, while other skills become redundant and are ultimately replaced by the better tools. The adoption of new technologies to save labor cost often represents an important way for firms to improve efficiency. However, firms do not always adopt new technologies upon their arrival. Indeed, 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 simple "technology-switching" 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 production. During this technology-adoption period, the firm's production is interrupted. Because the cost induced by the interruption is lower in bad times than in good times, firms tend to wait until bad times to undertake labor-technology substitution. As a result, firms with routine-task labor have a technology-switching option to improve their value in bad times, which leads to a lower exposure to systematic risk for these firms than firms without routine-task labor.

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, firms with a high share of routine-task labor have significantly lower market betas and future returns than their industry peers.

cannot explain my cross-sectional results between high-*RShare* firms and low-*RShare* firms, since these two groups of firms have very similar size and hence they should respond similarly to the incentives.

Appendix

A. Proofs

A.1. Proof of Proposition 1

Given that the payoff of exercising the switching option is monotonically decreasing in A_t (see equation (11)), and given that the process of A_t exhibits a positive serial correlation, we know that the optimal strategy to exercise the switching option is when A_t falls below a certain threshold A^* (see Dixit and Pindyck (1994) Section 4.1.D).

Under risk-neutral probability measure, $\frac{dA_t}{A_t} = -\sigma_x\sigma_\Lambda dt + \sigma_a d\hat{B}_t$ where $\hat{B}_t = \frac{\sigma_x(B_{xt}+\sigma_\Lambda t)+\sigma_\epsilon B_{\epsilon t}}{\sigma_a}$ is a Wiener process. Applying the Laplace transform for first passage time of drifted Brownian motion (see Shreve (2004) Section 8.3), we have $\hat{E}_t[e^{-r\tau}] = \left(\frac{A_t}{A^*}\right)^{-v}$, where $v = \sqrt{\left(\frac{1}{2}+\frac{\sigma_x\sigma_\Lambda}{\sigma_a^2}\right)^2 + \frac{2r}{\sigma_a^2}} - \left(\frac{1}{2}+\frac{\sigma_x\sigma_\Lambda}{\sigma_a^2}\right)$. To ensure that A^* is chosen optimally, the derivative of V_u^{so} with respect to A^* must be zero at all values of A_t. This gives the expression for A^* in Proposition 1, where $\xi = \frac{f_R - I_M r}{r(1+v)}$.

A.2. Proof of Proposition 3

I prove Proposition 3 following two steps.

Step 1: Calculate relation of portfolio beta and average cash flows.

Let $F_U(t)$ denote the set of unautomated firms at time t, and $F_A(t)$ the set of automated firms at time t. Denote $A_{u,t}$ and $A_{a,t}$ the cash flows of an unautomated firm and an automated firm at time t. The beta of a portfolio is the value-weighted average of the firm betas. Hence,

$$\begin{aligned}
\beta_U(t) &= \frac{\int_{F_U(t)} V_u \beta_{u,t} du}{\int_{F_U(t)} V_u du} \\
&= -v + \frac{(1+v)\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{u,t}) - vV_u^f}{\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{u,t}) - V_u^f + \xi A^{*v}\int_{F_U(t)} A_{u,t}^{-v} du} \\
&\leq -v + \frac{(1+v)\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{u,t}) - vV_u^f}{\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{u,t}) - V_u^f + \xi A^{*v}E(A_{u,t})^{-v}}.
\end{aligned} \tag{A.2.1}$$

The last inequality is achieved by using Jensen's inequality given that $v > 0$. Hence, we know that when $E(A_{u,t}) \to \infty$, $\beta_U(t) \to 1$ (using L'Hopital's Rule).

For an automated firm, depending on whether it is in the technology-adoption phase or the production phase, its value is between $\frac{e^{-(r+\sigma_x\sigma_\Lambda)T}}{r+\sigma_x\sigma_\Lambda}A_{a,t} - \frac{f}{r}$ (newly-automated) and $\frac{1}{r+\sigma_x\sigma_\Lambda}A_{a,t} - \frac{f}{r}$ (goods-producing). Hence,

$$\beta_A(t) = \frac{\int_{F_A(t)} V_a \beta_{a,t} da}{\int_{F_A(t)} V_a da} \in \left[1 + \frac{V_a^f}{\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{a,t}) - \frac{f}{r}}, 1 + \frac{V_a^f}{\frac{e^{-(r+\sigma_x\sigma_\Lambda)T}}{r+\sigma_x\sigma_\Lambda}E(A_{a,t}) - \frac{f}{r}}\right]. \tag{A.2.2}$$

As long as $E(A_{a,t})$ is bounded and $E(A_{u,t})$ increases without an upper bound over time, after sufficiently long time t, we will have $\beta_U(t) \to 1$ and$\beta_A(t) > 1$. In other words, $\beta_U(t) < \beta_A(t)$.

Step 2: Prove that as $t \to \infty$, $E(A_{u,t}) \to \infty$ and $E(A_{u,t})$ is bounded.

Note that $E(A_{u,t}) = E(A_t | \min_{0\le s\le t} A_s \ge A^*)$, $E(A_{a,t}) = E(A_t | \min_{0\le s\le t} A_s < A^*)$, and $A_t = A_0 \exp(-\frac{1}{2}\sigma_a^2 t + \sigma_a B_t)$. Denote $\mu = -\frac{1}{2}\sigma_a^2$ and $\sigma = \sigma_a$ to simplify notation. Let $W_t = -B_t$. Then, W_t is also a Wiener process. Hence,

$$E(A_{u,t}) = A_0 E\left[e^{-\sigma W_t + \mu t} | \max_{0\le s\le t} W_s - \frac{\mu}{\sigma}s \le \frac{1}{\sigma}\log\frac{A_0}{A^*}\right]. \tag{A.2.3}$$

Denote $\theta = \frac{\mu}{\sigma}$ and $H = \frac{1}{\sigma}\log\frac{A_0}{A^*}$ to further simplify notation. Given that $A_0 > A^*$, $H > 0$.

By Girsanov theorem, if we use $Z_\theta(t) = \exp\left(\theta W_t - \frac{1}{2}\theta^2 t\right)$ to define another probability measure $\tilde{\mathbb{P}}$, then,

$$E[X] = \tilde{E}[X Z_\theta^{-1}(t)], \tag{A.2.4}$$

and $\tilde{W}_t = W_t - \theta t$ is a Wiener process under $\tilde{\mathbb{P}}$. Hence,

$$\begin{aligned} E(A_{u,t}) &= A_0 \frac{E\left[e^{-\sigma\tilde{W}_t} 1\{\max_{0\le s\le t}\tilde{W}_t \le H\}\right]}{E\left[1\{\max_{0\le s\le t}\tilde{W}_t \le H\}\right]} \\ &= A_0 \frac{\tilde{E}\left[e^{-\sigma\tilde{W}_t - \theta\tilde{W}_t - \frac{1}{2}\theta^2 t} 1\{\max_{0\le s\le t}\tilde{W}_t \le H\}\right]}{\tilde{E}\left[e^{-\theta\tilde{W}_t - \frac{1}{2}\theta^2 t} 1\{\max_{0\le s\le t}\tilde{W}_t \le H\}\right]} \\ &= A_0 \frac{g(-\sigma-\theta, H, t)}{g(-\theta, H, t)}, \end{aligned} \tag{A.2.5}$$

where

$$g(\alpha, H, t) = \tilde{E}\left[e^{\alpha\tilde{W}_t} 1\{\max_{0\le s\le t}\tilde{W}_s \le H\}\right]. \tag{A.2.6}$$

Using the joint density of $\tilde{W}_t$ and $\tilde{M}_t = \max_{0\le s\le t}\tilde{W}_s$ under $\tilde{\mathbb{P}}$, we can calculate $g(\alpha, H, t)$

explicitly (see Corollary 7.2.2. in Shreve (2004) for derivation):

$$\begin{aligned} g(\alpha, H, t) &= e^{\frac{1}{2}\alpha^2 t}\tilde{P}(\tilde{M}_t \leq H) \\ &= e^{\frac{1}{2}\alpha^2 t}\left[\Phi(-\alpha\sqrt{t} + \frac{H}{\sqrt{t}}) - e^{2\alpha H}\left(1 - \Phi(\alpha\sqrt{t} + \frac{H}{\sqrt{t}})\right)\right]. \end{aligned} \tag{A.2.7}$$

Plugging (A.2.7) into (A.2.5) and noting that $\theta = \frac{\mu}{\sigma} = -\frac{1}{2}\sigma_a$, we have

$$\begin{aligned} E(A_{u,t}) &= A_0 \frac{g(-\frac{1}{2}\sigma_a, H, t)}{g(\frac{1}{2}\sigma_a, H, t)} \\ &= A_0 \frac{\Phi(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}) - e^{-\sigma_a H}\left(1 - \Phi(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}})\right)}{\Phi(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}) - e^{\sigma_a H}\left(1 - \Phi(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}})\right)}. \end{aligned} \tag{A.2.8}$$

where $\Phi(x)$ is the cumulative density function of a standard Normal distribution. Note that when $t \to +\infty$, $\Phi(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}) \to 1$ and $\Phi(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}) \to 0$. Also note that $H = \frac{1}{\sigma_a}\log\frac{A_0}{A^*}$. Hence, when $t \to +\infty$, the nominator of (A.2.8) approaches $A_0(1 - e^{-\sigma_a H}) = A_0 - A^* > 0$, and the denominator approaches 0. Hence,

$$E(A_{u,t}) \to +\infty. \tag{A.2.9}$$

Similarly, for automated firms, using Girsanov theorem, we have

$$E(A_{a,t}) = A_0 \frac{h(-\sigma - \theta, H, t)}{h(-\theta, H, t)}, \tag{A.2.10}$$

where

$$h(\alpha, H, t) = \tilde{E}\left[e^{\alpha\tilde{W}_t} 1\{\max_{0 \leq s \leq t} \tilde{W}_s > H\}\right]. \tag{A.2.11}$$

Note that

$$g(\alpha, H, t) + h(\alpha, H, t) = \tilde{E}\left[e^{\alpha\tilde{W}_t}\right] = e^{\frac{1}{2}\alpha^2 t}. \tag{A.2.12}$$

Hence, using equation (A.2.7), we have

$$\begin{aligned} h(\alpha, H, t) &= e^{\frac{1}{2}\alpha^2 t} - e^{\frac{1}{2}\alpha^2 t}\left[\Phi(-\alpha\sqrt{t} + \frac{H}{\sqrt{t}}) - e^{2\alpha H}\left(1 - \Phi(\alpha\sqrt{t} + \frac{H}{\sqrt{t}})\right)\right] \\ &= e^{\frac{1}{2}\alpha^2 t}\left[1 - \Phi(-\alpha\sqrt{t} + \frac{H}{\sqrt{t}}) + e^{2\alpha H}\left(1 - \Phi(\alpha\sqrt{t} + \frac{H}{\sqrt{t}})\right)\right]. \end{aligned} \tag{A.2.13}$$

Plugging (A.2.13) into (A.2.10), we have

$$\begin{aligned} E(A_{a,t}) &= A_0 \frac{h(-\frac{1}{2}\sigma_a, H, t)}{h(\frac{1}{2}\sigma_a, H, t)} \\ &= A_0 \frac{1 - \Phi(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}) + e^{-\sigma_a H}\left(1 - \Phi(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}})\right)}{1 - \Phi(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}) + e^{\sigma_a H}\left(1 - \Phi(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}})\right)}, \end{aligned} \tag{A.2.14}$$

Given that that when $t \to +\infty$, $\Phi(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}) \to 1$ and $\Phi(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}) \to 0$, we have

$$E(A_{a,t}) \to A_0 e^{-\sigma_a H} = A^*. \tag{A.2.15}$$

Plugging (A.2.9) into (A.2.1) and plugging (A.2.15) into (A.2.2), we have that as $t \to \infty$,

$$\beta_U(t) \to 1 \tag{A.2.16}$$

and

$$\beta_A(t) \geq 1 + \frac{V_a^f}{\frac{1}{r+\sigma_x\sigma_\Lambda}A^* - \frac{f}{r}} > 1. \tag{A.2.17}$$

B. 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 the 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 next 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 (19).
- $Mach/Capital$ is the ratio of machinery and equipment at cost (FATE) to the gross value of property, plant, and equipment (PPEGT).
- $Mach/Struct$ is the ratio of machinery and equipment at cost (FATE) to the productive structure at cost, which is the sum of buildings (FATB), capital leases (FATL), and land (FATP). See Tuzel (2010) for a discussion on structural capital.
- *Cash Flow* is cash flows defined as earnings before extraordinary items (IB) plus depreciation (DP) and is normalized by capital stock (PPENT) at the beginning of the year.
- *Stock Ret* is firms' annual stock returns.
- *Op.Lev* is firms' operating leverage defined as the cost of goods sold (COGS) plus selling, general, and administrative expenses (SGA) divided by the firm's market value.
- *Op.Cost* is firms' operating cost defined as cost of goods sold (COGS) plus selling, general, and administrative expenses (SGA), and is normalized by total assets (AT).
- $Mkt.Lev$ is firms' financial leverage defined as the proportion of total debt to the market value of the firm. 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 the 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 ratio, respectively, defined following Fama and French (1992).
- I^M is firms' investment in machines, calculated as the real growth rate of machinery and equipment at cost (FATE).
- I^O is firms' investment in other capital, calculated as the real growth rate of firms' physical capital other than machinery and equipment (PPEGT - FATE).

- *Shock*: The 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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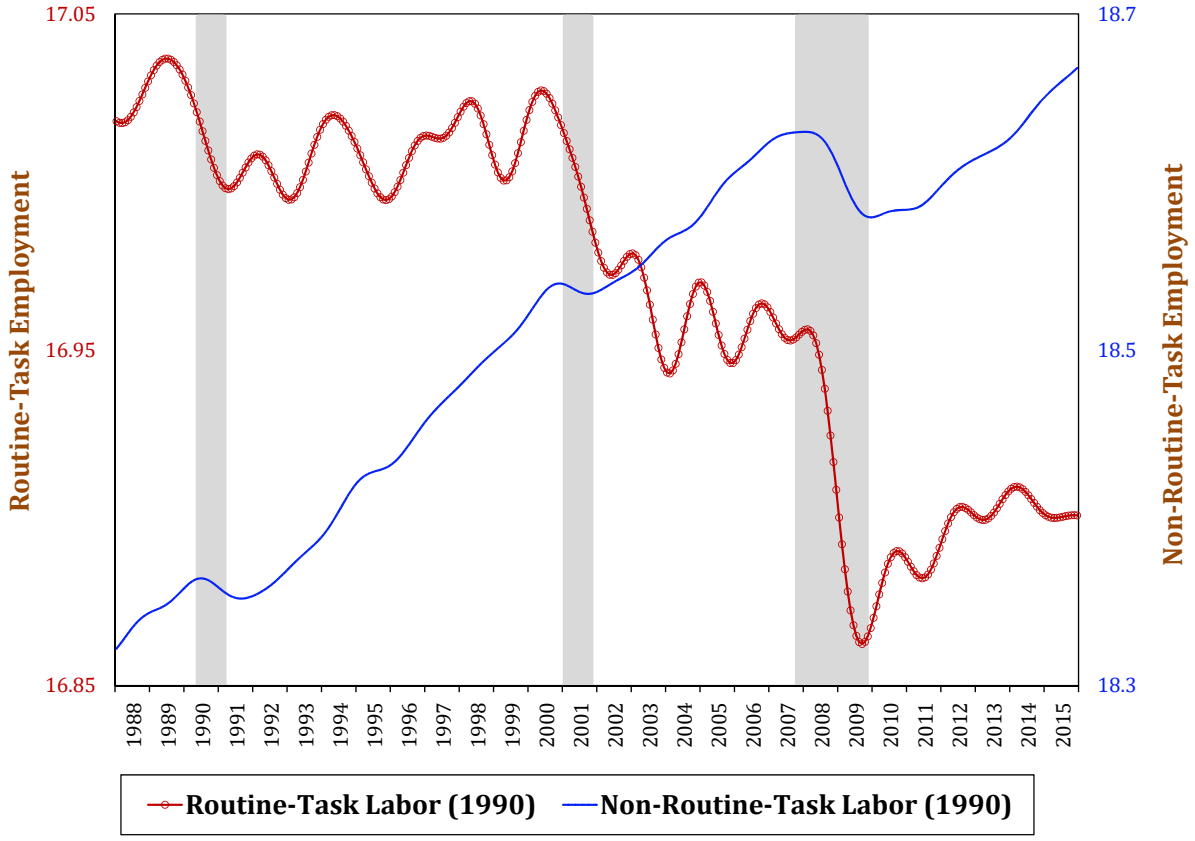

Figure 1. **Monthly employment of routine-task labor and non-routine-task labor classified based on 1990 employment distribution.** This figure illustrates the monthly employment of routine-task labor and non-routine-task labor using the Current Population Survey (CPS) monthly basic data. The data as well as a time-series consistent occupation code, *occ*1990, are obtained from the Integrated Public Use Microdata Series (IPUMS) database. Following Autor and Dorn (2013), I obtain the task skill data from the Dictionary of Occupation Titles and calculate the routine-task intensity (RTI) score for each occupation as in equation (18). I classify employees as *Routine-Task Labor (1990)* if their occupations' RTI scores are in the top quintile of the RTI distribution in the 1990 Census. I classify the rest of the employees as *Non-Routine-Task Labor (1990)*. The monthly employment is aggregated from the number of individuals in the occupations, weighted by the CPS sampling weights, and seasonally adjusted using the Census X12 ARIMA. The series are further logged and band pass filtered to remove only fluctuations at frequencies higher than 18 months. The shaded areas indicate the NBER recession months. This figure shows a consistent pattern to those by Jaimovich and Siu (2014) who classify routine-task labor based on three major occupation groups.

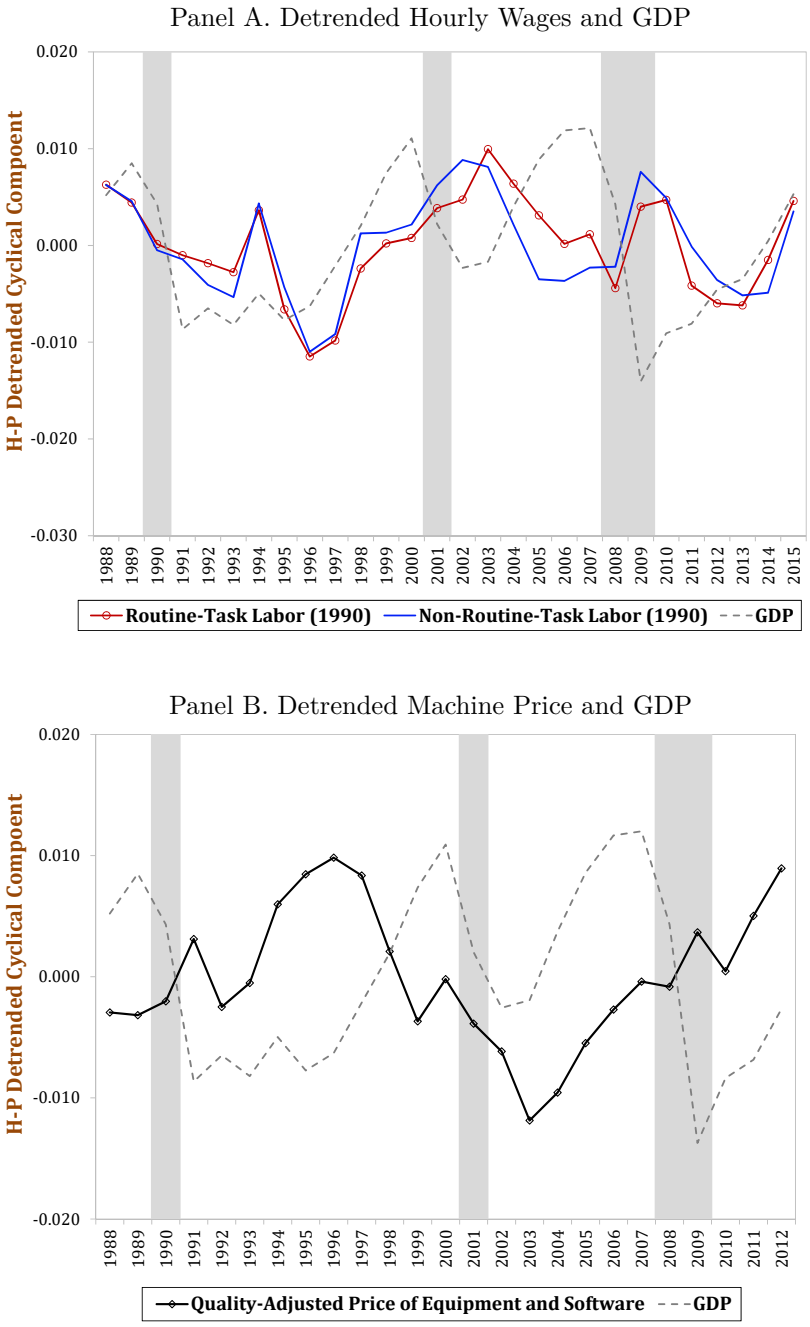

Figure 2. **Wages and machine price over the business cycle.** Panel A presents cyclicality of real hourly wages of routine-task labor and non-routine-task labor classified based on the 1990 employment distribution (see Figure 1 for definitions). The two series of hourly wages are aggregated from the individual level and weighted by the sample personal earnings weights, using the sample of the Current Population Survey Outgoing Rotation Group. Panel B presents the quality-adjusted price of equipment and software provided by Ryan Isaelsen. 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 were first constructed by Gordon (1990) and later extended by Israelsen (2010). All series are real, logged, and filtered to extract the cyclical component using the Hodrick-Prescott filter. The shaded areas indicate recession years based on the NBER Business Cycle Dates.

Table 1
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 the top quintile of the distribution in that year. See Section 2 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* represents 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 under SOC classification in 1999-2014. *Routine-task labor* is a dummy variable that equals one if the occupation is classified as routine-task labor in 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 other 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 (see Hirsch and MacPherson (2003)).

Panel A: Routine-Task Labor in Occupation Groups

	Management	Professional	Sales	Clerk	Service	Agriculture	Production	Total
Routine Labor	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 2
Summary Statistics of Firms

This table presents the summary statistics. Panel A reports the mean and standard deviation of the share of routine-task labor (*RShare*) for all matched Compustat firms by industry 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 (19). *Sector* is at the SIC 1-digit industry sector 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 the gross value of property, plant and equipment. *Mach/Struct* is the ratio of machinery and equipment at cost to productive structure at cost (i.e., buildings, capital leases, and land). *Op. Cost* is firms' operating cost measured by the sum of cost of goods sold (COGS) and selling, general & administrative expense (SG&A) normalized by the firms' total assets. *Op. Lev* is firms' operating leverage measured by the sum of COGS and SG&A divided by firm's market value. *Cash Flow*, *Size*, *B/M*, and *Mkt. Lev* represent cash flows, market capitalization, book-to-market ratio, and financial leverage, respectively. All variables are winsorized at the 1% level (0.5% in each tail of the distribution). See Appendix B for more details on the definitions of variables. Panel C shows the year-over-year transition probability matrix of a firm moving from one *RShare* quintile to another.

Panel A: Firm *RShare* by Sectors

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 *RShare* within Industry

Quint.	RShare	Mach/Capital	Mach/Struct	Cash Flow	Op. Cost	Op. Lev	B/M	Size	Mkt. Lev
L	0.02	0.75	5.48	−0.25	1.06	1.66	0.63	12.77	0.17
2	0.06	0.73	4.42	0.13	1.07	1.71	0.64	13.08	0.20
3	0.12	0.73	4.36	0.28	1.13	1.96	0.67	13.11	0.22
4	0.20	0.72	3.87	0.32	1.20	2.10	0.69	13.10	0.23
H	0.39	0.71	3.76	0.40	1.27	2.31	0.72	12.78	0.23

Panel C: Transition Probabilities across Portfolios Sorted by *RShare* within Industry

	Next Year				
Current Year	L	2	3	4	H
L	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
H	0.02	0.02	0.04	0.15	0.76

Table 3

Response of Firm Machinery Investment to Aggregate Shocks

This table shows the response of investment to aggregate shocks for firms with different shares of routine-task labor, *RShare*. The sample period is 1990-2014. *Investment in Machines* is the real growth rate of machinery and equipment at cost, *Investment in Other Capital* is the real growth rate of property, plant, and equipment at cost excluding machinery and equipment at cost. $RShare_{t-1}$ is firms' share of routine-task labor in the previous year. $Shock_t$ is the growth rate of real GDP value-added. Ind is the Fama-French 17 industry classification. Firm characteristics controls include Tobin's Q, market leverage, cash flows, cash holdings, and total assets in the previous year. See Appendix B for definitions of these variables. All variables are standardized so that the mean is 0 and the standard deviation is 1. All standard errors are clustered at the firm level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	Investment in Machines		Investment in Other Capital	
	(1)	(2)	(3)	(4)
$\text{RShare}_{t-1} \times \text{Shock}_t$	-0.012^{**}	-0.010^{**}	-0.006	-0.004
	(0.006)	(0.005)	(0.005)	(0.005)
RShare_{t-1}	0.003	0.002	-0.003	-0.003
	(0.008)	(0.008)	(0.009)	(0.009)
Firm Characteristics	N	Y	N	Y
Firm FE	Y	Y	Y	Y
Ind×Year FE	Y	Y	Y	Y
Observations	37,503	37,503	37,503	37,503
Adjusted R^2	0.357	0.407	0.312	0.340

Table 4
Response of Establishment Routine-Task Employment to Aggregate Shocks

Panel A shows the response of routine-task employment to aggregate shocks at the establishment level. *Chg.* $Emp^{R}_{t-3,t}$ is the establishment's 3-year change in employment of routine-task labor normalized by the average of the establishment's routine-task employment in the current year and three years earlier. Establishments that have zero percent or one hundred percent routine-task labor throughtout the three years are excluded. *Chg.* $RShare^{Est,Emp}_{t-3,t}$ and *Chg.* $RShare^{Est,Wage}_{t-3,t}$ are the 3-year changes in the establishment's employment-based share of routine-task labor and total-wage-based share of routine-task labor, respectively. An establishment's employment-based and total-wage-based share of routine-task labor are defined similar to firms' *RShare* in equation (19). 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, which restricts the sample period for this test to be 1996-2014. Establishments that experience changes in detailed industry classification from $t-3$ to t are excluded. In addition, OES data provide hourly wages since 1998, which makes *Chg.* $RShare^{Est,Wage}_{t-3,t}$ available only for 2001-2014. $RShare_{t-3}$ is the establishment's parent firm's *RShare* three years before. $Shock_{t-3,t}$ is the growth rate of real GDP value-added from $t-3$ to t. Panel B shows the response of the relation between firms' routine-task employment and investment to aggregate shocks. $I_{t-3,t}$ is the firms 3-year investment rate in machines in Columns (1) and (2) and 3-year investment in other capital in Columns (3) and (4). *Ind* is the Fama-French 17 industry classification. *State* is the state in which the establishment is located. All variables are standardized so that the mean is 0 and the standard deviation is 1. All standard errors, reported in parentheses, are clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Response of Routine-Task Employment

Dep. Var.	Chg. $\text{Emp}^{R}_{t-3,t}$	Chg. $\text{RShare}^{Est,Emp}_{t-3,t}$	Chg. $\text{RShare}^{Est,Emp}_{t-3,t}$ (2001-2014)	Chg. $\text{RShare}^{Est,Wage}_{t-3,t}$ (2001-2014)
	(1)	(2)	(3)	(4)
$\text{RShare}_{t-3}\times$ $\text{Shock}_{t-3,t}$	0.024**	0.028**	0.023**	0.024**
	(0.010)	(0.013)	(0.011)	(0.011)
RShare_{t-3}	−0.431***	−0.555***	−0.594***	−0.586***
	(0.027)	(0.042)	(0.047)	(0.050)
Firm FE	Y	Y	Y	Y
Ind×Year FE	Y	Y	Y	Y
State×Year FE	Y	Y	Y	Y
Observations	71,767	71,767	68,269	68,269
Adjusted R^2	0.139	0.150	0.147	0.153

Table 4 — *Continued*

Panel B: Response of Relation Between Routine-Task Employment and Machinery Investment				
$I_{t-3,t}$	Investment in Machines		Investment in Other Capital	
Dep. Var.	Chg. $\text{Emp}^{R}_{t-3,t}$	Chg. $\text{RShare}^{Est,Emp}_{t-3,t}$	Chg. $\text{Emp}^{R}_{t-3,t}$	Chg. $\text{RShare}^{Est,Emp}_{t-3,t}$
	(1)	(2)	(3)	(4)
$\text{RShare}_{t-3}\times\text{Shock}_{t-3,t}\times\text{I}_{t-3,t}$	0.030***	0.017**	0.005	−0.007
	(0.010)	(0.007)	(0.011)	(0.013)
$\text{RShare}_{t-3}\times\text{Shock}_{t-3,t}$	−0.002	0.014	−0.003	0.013
	(0.013)	(0.013)	(0.013)	(0.013)
$\text{RShare}_{t-3}\times\text{I}_{t-3,t}$	−0.022	−0.015	−0.004	0.001
	(0.015)	(0.009)	(0.015)	(0.011)
$\text{Shock}_{t-3,t}\times\text{I}_{t-3,t}$	−0.039***	−0.021**	−0.037**	−0.023
	(0.013)	(0.009)	(0.015)	(0.015)
$\text{I}_{t-3,t}$	0.036**	0.014	0.029	0.018
	(0.017)	(0.011)	(0.018)	(0.013)
RShare_{t-3}	−0.477***	−0.556***	−0.475***	−0.555***
	(0.031)	(0.038)	(0.031)	(0.038)
Firm FE	Y	Y	Y	Y
Ind×Year FE	Y	Y	Y	Y
State×Year FE	Y	Y	Y	Y
Observations	50,248	50,248	50,248	50,248
Adjusted R^2	0.136	0.141	0.136	0.140

Table 5
Five Portfolios Sorted on *RShare* Within Industry

This table reports the time-series average of stock returns for five portfolios sorted on the 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 (23) following Liu, Whited, and Zhang (2009), 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 at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1991 to June 2014.

	L	2	3	4	H	H−L
			Mean Excess Returns			
$E[R] - r_f$ (%)	14.11***	13.17***	12.40***	12.32***	11.02**	−3.10*
	(4.99)	(4.51)	(4.51)	(4.41)	(4.32)	(1.70)
			Excess Unlevered Returns			
$E[R^{Unlev}] - r_f$ (%)	12.16***	10.74***	10.03***	9.88***	9.04***	−3.12**
	(4.35)	(3.81)	(3.70)	(3.52)	(3.48)	(1.53)
			DGTW-Adjusted Returns			
$E[R^{DGTW}]$ (%)	3.11*	2.83**	1.82	1.41	−0.24	−3.35**
	(1.63)	(1.32)	(1.33)	(1.42)	(1.25)	(1.44)

Table 6
CAPM Betas

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 at the 10%, 5%, and 1% level, 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***	1.15***	1.13***	1.09***	1.03***	−0.23***
	(0.05)	(0.04)	(0.06)	(0.06)	(0.07)	(0.05)
α (%)	4.08	4.06	3.40	3.67	2.79	−1.29
	(2.64)	(2.49)	(2.40)	(2.46)	(2.48)	(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***	1.45***	1.36***	1.35***	1.31***	−0.29***
	(0.11)	(0.10)	(0.08)	(0.10)	(0.08)	(0.06)
Avg. α (%)	3.40	2.78	3.48	2.92	1.64	−1.76
	(4.68)	(4.20)	(3.66)	(3.42)	(3.48)	(2.07)
Avg. R^2	0.77	0.79	0.80	0.80	0.77	0.31

Table 7

Panel Regressions of Annual Stock Returns and Conditional Betas 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 Appendix B for definitions of firm characteristics. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1991 to June 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: Annual Stock Returns					
RShare$_{t-1}$	-5.66**	-8.31***	-7.70***	-6.81***	-5.33**	-6.66***	-7.09***	-5.83**	-8.35***
	(2.28)	(2.37)	(2.35)	(2.30)	(2.28)	(2.33)	(2.33)	(2.33)	(2.43)
Op. Lev$_{t-1}$		2.00***							1.02***
		(0.20)							(0.29)
B/M$_{t-1}$			11.56***						6.92***
			(0.96)						(1.15)
Op. Cost$_{t-1}$				2.71***					-0.17
				(0.47)					(0.66)
Cash Flow$_{t-1}$					-0.37**				-0.20
					(0.16)				(0.16)
Size$_{t-1}$						-2.55***			-1.19***
						(0.21)			(0.21)
Mkt. Lev$_{t-1}$							16.14***		-2.44
							(1.91)		(2.54)
Stock Ret$_{t-1}$								-4.85***	-3.26***
								(0.72)	(0.71)
Ind×Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
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	0.11	0.10	0.10	0.10	0.10	0.10	0.11
				Panel B: Conditional Betas					
RShare$_{t-1}$	-0.48***	-0.52***	-0.50***	-0.48***	-0.45***	-0.52***	-0.52***	-0.48***	-0.46***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Op. Lev$_{t-1}$		0.02***							0.02**
		(0.01)							(0.01)
B/M$_{t-1}$			0.11***						-0.08**
			(0.03)						(0.04)
Op. Cost$_{t-1}$				-0.01					-0.11***
				(0.02)					(0.03)
Cash Flow$_{t-1}$					-0.04***				-0.04***
					(0.01)				(0.01)
Size$_{t-1}$						-0.09***			-0.09***
						(0.01)			(0.01)
Mkt. Lev$_{t-1}$							0.36***		0.20**
							(0.07)		(0.10)
Stock Ret$_{t-1}$								0.16***	0.20***
								(0.03)	(0.03)
Ind×Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
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	0.07	0.08

Table 8
Robustness of Industry Classification in Panel Regressions

Panel A reports the robustness check of the panel regressions on annual stock returns using alternative industry classifications. *Baseline* uses the Fama-French 17 industry classification. *FF49* uses the Fama-French 49 industry classification. *SIC1* and *SIC2* use the SIC 1-digit industry sector classification and SIC 2-digit industry classification, respectively. *HP50* and *HP100* use the 10-K text-based fixed industry classifications as in Hoberg and Phillips (2010) and Hoberg and Phillips (2015) with 50 and 100 industry categories, respectively. *No Ind.* means running the regression without industry fixed effects. Panel B conducts the panel regression on stock returns within each SIC 1-digit industry sector. All standard errors are clustered at the firm level and reported in parentheses. Firm control variables are listed in Table 7 and defined in Appendix B. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1991 to June 2014.

Panel A: Alternative Industry Classifications

	Baseline	FF49	SIC1	SIC2	HP50	HP100	No Ind.
RShare_{t-1}	-8.35^{***}	-6.30^{**}	-11.93^{***}	-6.54^{**}	-7.69^{***}	-6.56^{**}	-11.67^{***}
	(2.43)	(2.54)	(2.40)	(2.58)	(2.81)	(2.81)	(2.30)
Firm Control	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Yr
Observations	41,080	41,080	41,080	41,080	31,437	31,437	41,080
Adj. R^2	0.11	0.14	0.09	0.12	0.16	0.17	0.07

Panel B: Subsample by Industry Sectors

Sector	Mining	Construction	Manufacture	Transportation	Wholesale	Retail	Service
RShare_{t-1}	-3.22	-4.42	-13.45^{***}	1.37	-16.22^{*}	-9.25^{*}	-8.41
	(10.02)	(22.64)	(3.29)	(11.74)	(8.92)	(5.21)	(5.99)
Firm Control	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,550	509	23,274	2,173	1,648	3,975	7,864
Adj. R^2	0.27	0.21	0.07	0.16	0.09	0.13	0.08

Table 9

Robustness of Measurement Error in *RShare* for Panel Regressions

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 10% or not. 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. Firm control variables are listed in Table 7 and defined in Appendix B. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, 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 Coverage Ratio			
	Above 10%		Below 10%	
RShare_{t-1}	-6.70^{**}	-9.63^{***}	-4.91	-6.50^{*}
	(2.83)	(3.08)	(3.85)	(3..88)
Firm Control	N	Y	N	Y
Ind×Year FE	Y	Y	Y	Y
	Panel B: Subsample by Geographic Dispersion			
	Concentrated		Dispersed	
RShare_{t-1}	-19.91^{***}	-20.43^{**}	-6.90^{**}	-8.74^{***}
	(7.38)	(8.13)	(2.96)	(3.12)
Firm Control	N	Y	N	Y
Ind×Year FE	Y	Y	Y	Y
	Panel C: Subsample by Firm Size			
	Small		Large	
RShare_{t-1}	-9.10^{**}	-12.57^{***}	-2.25	-3.18
	(3.55)	(3.75)	(2.22)	(2.28)
Firm Control	N	Y	N	Y
Ind×Year FE	Y	Y	Y	Y

Table 10
Mean Excess Returns in Double Sorting

This table reports the portfolio sorting conditional on firms' characteristics. At the end of each June, firms in each Fama-French 17 industry are first sorted into three bins based on a firm characteristic. Within each bin, I further sort firms into five equally-weighted portfolios based their *RShare*, resulting in fifteen portfolios in total. For each category of *RShare* (i.e., L, 2, 3, 4, H), I report the the average excess returns across the sorts of the firm characteristic. Column (1) reports the unconditional sorting results. Excess returns are monthly returns minus the 1-month Treasury bill rate. See Appendix B for definitions of firm characteristics. Newey-West standard errors 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 at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1991 to June 2014.

	Uncond. (1)	Op. Lev (2)	B/M (3)	Op. Cost (4)	Cash Flow (5)	Size (6)	Mkt. Lev (7)	Lag Ret (8)
L	14.11	14.65	14.19	14.23	14.41	14.06	13.92	14.79
2	13.17	13.41	13.64	13.45	13.14	13.01	13.98	12.86
3	12.40	12.52	12.34	12.70	12.55	12.96	11.90	12.34
4	12.32	12.01	12.39	11.69	12.14	12.66	11.85	12.50
H	11.02	10.71	10.35	11.03	11.22	11.09	11.43	11.38
H−L	−3.10*	−3.94**	−3.85**	−3.20**	−3.19**	−2.97*	−2.48*	−3.41**
	(1.70)	(1.62)	(1.63)	(1.62)	(1.31)	(1.59)	(1.50)	(1.58)

Table 11
Exercise of Switching Options in Recessions

This table reports the time series of operating leverage and market beta for 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 A reports the time-series around recessions. Panel B reports results in a falsification test by using expansions instead of recessions. In Panel A (Panel B), in the year 2000 and 2007 (1996 and 2003), firms in each Fama-French 17 industry are sorted into five equally-weighted portfolios based on their *RShare* in the year prior to recessions or expansions. The portfolio formation maintains the same for four years. Firms are required to have all information available for the four years. *Machine-to-Employment Ratio* is the ratio of machinery and equipment at cost and total number of employees at $ 1 million per employee. *Operating Cost* is the sum of cost of goods sold and selling, general & administrative expense normalized by total assets. *Portfolio beta* is the regression coefficient of regressing the portfolios' monthly 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 at the 10%, 5%, and 1% level, respectively.

Panel A: Portfolios Formed in Year Prior to Recessions				
	$t-1$	Recession	$t+1$	$t+2$
		Machine-to-Employment Ratio		
H	0.067	0.071	0.077	0.079
L	0.080	0.083	0.089	0.090
H−L	−0.014*	−0.012	−0.011	−0.011
	(0.008)	(0.008)	(0.009)	(0.009)
		Operating Cost		
H	1.257	1.295	1.233	1.206
L	1.117	1.171	1.104	1.079
H−L	0.141**	0.124	0.128*	0.127
	(0.071)	(0.075)	(0.074)	(0.077)
		Portfolio Beta		
H	0.709	1.416	1.156	1.233
L	0.992	1.492	1.354	1.290
H−L	−0.283**	−0.075	−0.198**	−0.057
	(0.115)	(0.097)	(0.085)	(0.112)

Table 11 — *Continued*

Panel B: Portfolios Formed in Year Prior to Expansions (Falsification Test)				
	$t-1$	Expansion	$t+1$	$t+2$
		Machine-to-Employment Ratio		
H	0.058	0.059	0.060	0.061
L	0.072	0.074	0.076	0.079
H−L	−0.014*	−0.016**	−0.017**	−0.017**
	(0.008)	(0.008)	(0.008)	(0.008)
		Operating Cost		
H	1.247	1.271	1.289	1.264
L	1.142	1.126	1.120	1.129
H−L	0.104*	0.145**	0.168***	0.135**
	(0.061)	(0.063)	(0.063)	(0.061)
		Portfolio Beta		
H	0.828	0.912	0.870	0.636
L	1.058	1.175	1.102	0.860
H−L	−0.231*	−0.263**	−0.231***	−0.225**
	(0.125)	(0.114)	(0.063)	(0.100)