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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 such 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 stock returns.

LABOR ECONOMISTS ARGUE THAT IN recent decades, automation has increasingly replaced workers who perform procedural and rule-based tasks, that is, routine tasks. In addition, Jaimovich and Siu (2014) find that the disappearance of routine-task jobs has occurred mainly during recessions, with such job disappearance accounting for almost all job loss in the three most recent recessions.[1]

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

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Connecting these findings to a firm's production, it seems that adopting machines to replace routine-task labor, that is, labor-technology substitution, is an economically significant 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 the 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)), opportunities for labor-technology substitution have two distinctive features in my model. First, labor-technology substitution features cost saving rather than scale expansion. Second, labor-technology substitution may interrupt firm production. For example, adopting technologies is known to be accompanied by plant restructuring (Cooper and Haltiwanger (2006)), worker retraining (Atkin et al. (2017)), and organizational restructuring (Bresnahan, Brynjolfsson, and Hitt (2002)), all of which are likely to interrupt firm production. Given this interruption, firms optimally choose to switch technologies when their productivity is low. Hence, if the economy experiences a negative productivity shock, firms that have not yet switched technologies (due to their superior productivity in the past) are able to do so. The increase in firm value resulting from this switching acts as a hedge against negative shocks and lowers firms' risk premia. In other words, firms with a higher share of routine-task labor maintain 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 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 (BLS). The OES microdata provide employment and wages for over 800 detailed occupations in 1.2 million establishments in the United States over three-year cycles, covering 62% of total national employment from 1990 to 2014. Following the labor economics literature (Autor and Dorn (2013)), I classify occupations into routine-task labor and nonroutine-task labor. 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. I compare firms with different *RShare* within industry sector to ensure that *RShare* does not simply reflect the heterogeneous business models across industry sectors.

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 my model's assumption that routine-task labor and machines are substitutes. High-*RShare* firms also have higher operating costs and higher operating leverage, which is consistent with the model's assumption that routine-task labor

jobs over the past 30 years include clerks, production line assemblers, travel agents, bank tellers, and tax preparers. See Acemoglu and Autor (2011) for a review of the literature on decreasing routine-task jobs.

is more costly to use than machines. Finally, high-*RShare* firms have higher cash flows. This relation is consistent with the model's implication that firms with higher cash flows face a higher opportunity cost for switching technologies and thus are more likely to retain their routine-task labor than to switch to machines.

The main empirical findings in this paper are twofold. First, I find strong negative relations between firms' *RShare* and their exposure to systematic risk and expected stock returns. I use time-invariant and time-varying market betas (Lewellen and Nagel (2006)) in the Capital Asset Pricing Model (CAPM) as my main proxies for firms' exposure to systematic risk. As alternative proxies, I examine the beta of aggregate cash flow news and the beta of GDP growth. 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 betas and future excess returns. In all specifications, 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 −3.9% per year.

My second main empirical finding is that, in response to unfavorable aggregate economic shocks, high-*RShare* firms increase the extent of their labor-technology substitution more than low-*RShare* firms. Specifically, when I compare firms in the cross-section, I find that when GDP growth is low, high-*RShare* firms, compared to their low-*RShare* industry peers, (1) invest more in machines (especially in computers), (2) reduce more routine-task labor, and (3) reduce even more routine-task labor if they invest more in machines. To the best of my knowledge, this is the first empirical evidence to show that routine-task labor is *substituted* by machines within firms during economic downturns.[2] Moreover, these results suggest that high-*RShare* firms have more abundant technology-switching options that can be exercised during economic downturns.

To strengthen the link between my model's mechanism and the cross-sectional risk premia, I test two additional predictions of the model. First, I show that high-*RShare* firms cut operating costs more and lose less market value than low-*RShare* firms over recessions. In contrast, I do not find such differences between firms over expansions. Hence, high-*RShare* firms do seem to be able to better hedge their value against unfavorable economic shocks through exercising switching options, resulting in lower expected returns for these firms. Second, my model predicts that high-*RShare* firms have higher operating leverage, which offsets part of the hedging effect of the switching option. Hence, if operating leverage is controlled for, high-*RShare* firms should have even lower betas than low-*RShare* firms. I confirm this prediction in tests that control for the linear and nonlinear associations between operating

[2] Most studies on routine-biased technological change use individual-level 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.

leverage and *RShare*. These findings distinguish my model's mechanism from alternative explanations based solely on the operating leverage channel.

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 treat investment opportunities as growth options (see Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), and Kogan and Papanikolaou (2014), among others). This paper shows that investment opportunities, fueled by labor-saving technologies, can also represent technology-switching options. While growth options increase firm output and are risky options, technology-switching options increase firm efficiency and are hedging options.[3] Thus, my model complements existing theories and improves our understanding of the links between firms' investment opportunities and stock returns.

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 length of time for a new technological product to diffuse from 10% to 90% (of the full adoption level) is over 10 years (see many examples in Greenwood (1999) and Manuelli and Seshadri (2014)). Indeed, firm investment in adopting technologies can be affected by other 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 (Greenwood, Hercowitz, and Krusell (1997), Papanikolaou (2011)), incorporating the nuances of technology adoption, such as technology-switching options, is a valuable addition to investment-based asset pricing theory.[4]

My findings also contribute to a growing literature on labor heterogeneity and the cross-section of stock returns (see Gourio (2007), Chen, Kacperczyk, and Ortiz-Molina (2011), Kuehn, Simutin, and Wang (2017), and Tuzel and Zhang (2017), among others). Eisfeldt and Papanikolaou (2013) and Donangelo (2014) derive firm risk by connecting employees' outside options to priced technology frontier shocks and to aggregate economic shocks, respectively. In contrast to these studies, my paper derives the effect of labor heterogeneity on firm risk directly through the firm's real options rather than through their employees' outside options. Ochoa (2013) and Belo et al. (2017) derive firm risk by assuming that higher skilled workers impose a higher adjustment cost on firms, where the difference in adjustment cost between skilled and unskilled workers is either fixed or unrelated to the business cycle. My work differs from these studies by exploring the *procyclical* opportunity cost of labor-technology substitution, which links firm risk directly to aggregate economic shocks.

Finally, this paper draws intuition from and also contributes to the economics literature on routine-biased technological change (RBTC). The central theme of

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

[4] 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.

RBTC is that technologies can directly replace routine-task jobs. Acemoglu and Autor (2011) show that such skill-replacing technologies are essential for explaining changes in the distribution of employment over the last four decades, such as job polarization. Goos, Manning, and Salomons (2014) argue that these changes in employment distribution cannot be explained by the traditional theory of skill-biased technological change, which focuses on the complementarity between technology and skilled labor. My work shows that the central theme of RBTC has important implications for asset pricing. In addition, by linking the cost and benefit of replacing routine-task labor with machines to aggregate productivity, my theoretical and empirical findings establish a mechanism for RBTC to be more pervasive during economic downturns. This mechanism not only helps explain the asset pricing findings in my paper, but also sheds light on recent empirical findings in the RBTC literature, such as Jaimovich and Siu (2014), who find that RBTC appears to be episodic around recessions, and Hershbein and Kahn (2018), who find that occupations became less routine after the Great Recession.

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

I. Model

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

A. 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, and thus a firm's value is equal to the market value of its equity.

Each firm has one production project. Firms differ from each other in two respects: cash flows and type.[5] The cash flows generated by firm j at time t are given by

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

[5] This model abstracts from growth options by assuming that all firms are "single-project" firms. This assumption focuses the model on firms' cost reduction rather than scale expansion (e.g., taking on new projects). Hence, the empirical implications of this model are primarily in the cross-section of firms rather than in the aggregate time series. In the Internet Appendix, which is available in the online version of the article on the *Journal of Finance* website, I add growth options by allowing for the random arrival of new projects (Berk, Green, and Naik (1999), Kogan and Papanikolaou (2014)). This extended model, which is much less tractable, maintains the cross-sectional predictions of the simple model and can also generate cyclical aggregate investments, which the simple model cannot generate.

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

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

where B_{xt} and $B_{\epsilon t}$ are Wiener processes that are 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, unautomated firms and automated firms, which are 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 nonroutine tasks are performed. Second, each firm requires fixed units of nonroutine-task labor such as managers and janitors to perform the nonroutine 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 that 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 become *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 machines on the initiation date. I assume that using machines reduces the 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 nonroutine-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, $I_M < \frac{f_R}{r}$.[6] For simplicity, I assume that the process of the firm-specific shock is not affected by a firm switching type. Finally, all machines, once they are purchased and customized to the firm's production, have zero resale value.

The key force that constrains the firm from immediately adopting machines is that it takes the firm T units of time to adapt the technologies embodied in the machines. Thus, a newly automated firm does not generate any cash flows until T periods have passed. The cost-saving benefit of switching to automation

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

and the opportunity cost due to production interruption constitute the trade-off that the firm faces when switching technologies.

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

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

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

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

B. 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

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

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

B.1. Value of Automated Firms

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

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

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

B.2. 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*

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

and the value of the unautomated project is

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

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

Appendix A 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.*

C. Firm Risk

A firm's equity beta is defined as the covariance between the firm's value and the stochastic discount factor rescaled to one for revenue.[7] 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 $\beta_u^{so} = -\frac{(1+\upsilon)\xi A^{*\upsilon}A_t^{-\upsilon}}{V_u^{so}} < 0$.

[7] That is, $\beta = -\frac{\sigma_\Lambda}{\sigma_x}\frac{\text{Cov}[\frac{dV}{V}, \frac{d\Lambda}{\Lambda}]}{\text{Var}[\frac{d\Lambda}{\Lambda}]}$. Multiplying and dividing this equation by $d\log A$, we have $\beta = \frac{d\log V}{d\log A}$.

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

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

Further defining a firm's operating leverage as $\frac{V^f}{V}$ (Novy-Marx (2011)), we have the follow corollary.

COROLLARY 2: *(Sources of heterogeneity in firm risk.) The cross-sectional comparison of betas between an unautomated firm and an automated firm is subject to two channels, operating leverage and the switching option:*[8]

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

Given that $\beta_u^{so} < 0$, the effect of the switching option channel is straightforward: unautomated firms have a 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, e.g., 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. On the other hand, unautomated firms have on average higher cash flows than automated firms due to the optimal exercise of the switching option. In particular, 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 relative to automated firms.

To assess how the operating leverage channel contaminates the hedging effect of the switching option channel on an average firm's risks, 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 $A_0 > A^*$.*

[8] The coexistence of the operating leverage channel and the real options channel is generic in investment-based asset pricing models. These two channels often have opposing effects on firm risks (see Hackbarth and Johnson (2015) for a detailed discussion).

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 given time, firms that remain unautomated are *survivors* with a path of cash flows above A^* at each point in time in the past. Due to this selection based on the 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 declines and the hedging effect of the switching option channel dominates the comparison of portfolio betas. I formalize this rationale in a proof in Appendix A.

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

D. Discussions on Model Implementation

When empirically testing this model, one should exercise caution for several reasons. The first is that, for simplicity, the model shuts down growth options for firms. By doing so, the model focuses on firms' investment in cost saving (in bad times), rather than scale expansion (most likely in good times). As long as growth opportunities are not perfectly correlated with firms' use of routine-task labor (which is supported by the data), this model can be well identified in the cross-section. Hence, in my tests of the model's mechanism, for example, I examine unautomated firms' response to aggregate shocks while using automated firms' response as a counterfactual. The differential responses between these firms serve the purpose of identification. I also control for measures of firms' growth options in these tests.

The second reason for caution is that industries differ significantly in their average share of routine-task labor (see Table II). However, the cross-industry difference in this share between an average retail firm and an average construction firm (with a share of routine-task labor of 25% and 7%, respectively) may not properly capture the retail firm's ability to switch technology and catch up with the construction firm. Rather, the difference may represent the differential business models of these two sectors, which can hardly be assimilated in the short run. For this reason, I restrict all of the empirical analyses in this paper to within-industry comparisons.

The last reason for caution is that, for simplicity, my model assumes that labor and machines are two comparable input factors with fixed prices. To rule out confounding explanations stemming from the dynamics of factor prices or from heterogeneous fixed adjustment costs for these factors, in Section III.C.6 I present supporting empirical evidence to differentiate my model's mechanism from these confounding hypotheses.

II. Measuring a Firm's Routine-Task Labor

A. Data and Methodology

My model suggests that both 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 *RShare*. I relegate additional details to Appendix B.

I construct firm *RShare* in three steps. First, I decompose each firm's labor cost by its workers' occupations. Second, I identify the occupations in each year that can be regarded as routine-task jobs. I then construct a firm's *RShare* following the definition above.

To obtain firms' occupational composition, I use data at the establishment-occupation level provided by the OES program of the BLS. This data set covers surveys that track employment by occupations in approximately 200,000 establishments every six months over three-year cycles from 1988 to 2014. On average, these data represent 62% of the nonfarm employment in the United States. These 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, these 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 wage for each occupation in each establishment from 1998 onward. The OES microdata do not have wage information before 1998. Hence, for years before 1998, I estimate hourly wages from the Census Current Population Survey Merged Outgoing Rotation Groups (CPS-MORG).[9] The total wage paid to an occupation in an establishment is simply the product of employment and the hourly wage.

I aggregate establishments to Compustat firms using the following matching procedure. First, I match establishments to Compustat firms based on EIN. Second, I match the legal name and trade name of establishments to Compustat firms' names. One 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*

[9] See the Internet Appendix for further details on this wage imputation.

and increase the standard errors in my analysis. To mitigate this concern, I perform a third matching procedure. Specifically, I identify establishments that are matched to a Compustat firm by name but not by EIN. I regard the EINs of these establishments as also belonging to the Compustat firm. I then search other establishments that have these EINs and match them to the Compustat firm. I refer to this last step as "EIN-induced" matching.[10]

A firm's labor composition in year t is captured by the occupation composition of 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 three-year cycles, this methodology provides better coverage of a firm's operation than only using firms' establishments in year t. This procedure identifies the occupation composition for an average of 4,297 Compustat firms in each year from 1990 to 2014.

Next, I identify occupations that can be classified as routine-task labor. My methodology is based on a procedure commonly used in the labor economics literature and is closest to Autor and Dorn (2013). Specifically, I use the revised fourth edition [1991] of the U.S. Department of Labor's Dictionary of Occupational Titles (DOT) to capture each occupation's required level of skill in performing *abstract*, *routine*, and *nonroutine manual* tasks (scaled from 1 to 10).[11] I next aggregate the DOT occupations to the OES occupation level using the weighting method proposed by Autor, Levy, and Murnane (2003). See the Internet Appendix for more details. Following Autor and Dorn (2013), I define the routine-task intensity (RTI) score for each OES occupation as

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

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

Routine-task labor is defined as follows. In each year, I construct current year's labor force using all workers in the OES sample in the current year as well as in the previous two years.[12] I then sort all workers in the current year's labor force based on their occupation's RTI score. I define workers as routine-task labor if their RTI score falls in the top quintile of the distribution for that

[10] For these EIN-induced matches, I also require that the similarity score between the establishments' legal names or trade names and the Compustat firms' names to be greater than 50%. Some states allow establishments that use professional payroll firms to report the payroll firms' EINs instead of the establishment owners' EINs. Accordingly, I hand-collect the names and EINs of professional payroll firms, and I exclude establishments that have legal names or EINs that match the payroll firms in the EIN-induced matching.

[11] Specifically, abstract skill is measured by a combination of mathematical skills and the skills in direction, control, and planning. Routine skill is measured by a combination of finger dexterity skills and skills in setting limits, tolerances, or standards. Nonroutine manual skill is measured by eye-hand-foot coordination skills. See the Internet Appendix for more details. To avoid using look-ahead information, for the years before 1991 I use information from the fourth edition [1977] of the DOT to construct the task skill measures.

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

year.[13] 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 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$^{\text{th}}$ percentile of RTI scores for the labor force in year t, and $emp_{j,k,t}$ and $wage_{j,k,t}$ are the number of employees and the hourly wage of occupation k in firm j and year t, respectively.

I finalize my sample selection by excluding conglomerates to suit the within-industry analyses (as discussed in Section I.D) and 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. My final sample consists of 45,556 firm-years with stock return information in 17 industries based on the Fama and French (1997) classification.

B. A Glance at Routine-Task Labor

Panel A of Table I 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.

Panel B summarizes the characteristics of occupations that are routine-task jobs. We see that routine-task jobs are uncorrelated with jobs that can be outsourced based on the offshorability measure created by Acemoglu and Autor (2011). This result is consistent with Blinder and Krueger (2013), who argue that any job that does not need to be done in person can ultimately be outsourced, regardless of whether it is routine or nonroutine. The labor economics 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 between the routine measures and occupations' median wages and skills. In particular, note that nonroutine-task labor includes both skilled workers and some unskilled workers such as manual workers. Finally, there is no significant correlation between routine-task jobs and union coverage, suggesting that unions are unlikely to

[13] The OES survey changed design in 1996, making it difficult to find a sample to represent the total labor force in that year. I therefore use the 1995 definition of routine-task labor to proxy for the total labor force in 1996.

Table I

Routine-Task Labor

Panel A presents the time series average of the share of routine-task labor for aggregate occupational groups using data at the establishment-occupation level provided by the 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 II for the definition of the routine-task intensity score. *Emp in 2014* is total employment in millions as of 2014. See the Internet Appendix for details on grouping occupations. Panel B presents the time series average of the correlation between different characteristics of occupations under Standard Occupational Classification over 1999 to 2014. *Routine-task labor* is a dummy variable equal to 1 if the occupation is classified as routine-task labor in that year and 0 otherwise. *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 from the OES website (www.bls.gov/oes/tables.htm). *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 (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

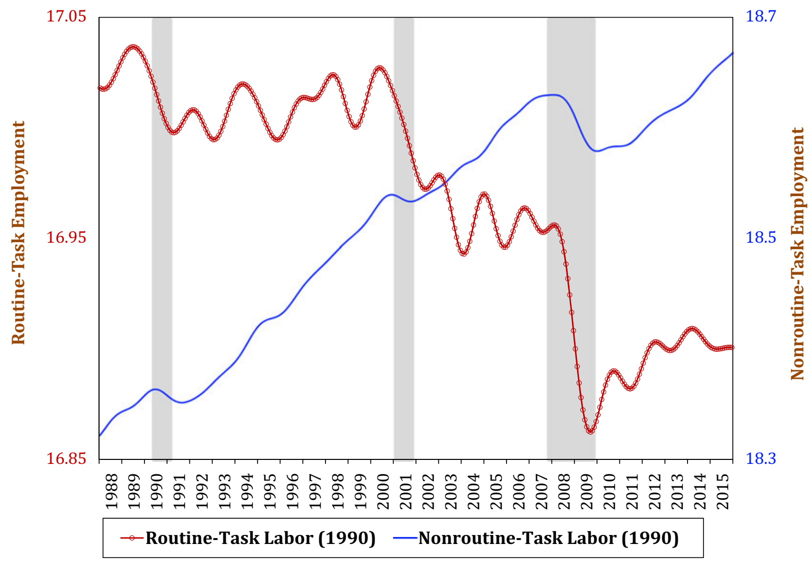

Figure 1. Monthly employment of routine-task labor and nonroutine-task labor. This figure illustrates the monthly employment of routine-task labor and nonroutine-task labor using Current Population Survey (CPS) monthly basic data. The CPS data as well as a time series consistent occupation code, *occ*1990, are obtained from the Integrated Public Use Microdata Series (IPUMS) database. Following Autor and Dorn (2013), I obtain 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 employees as *NonRoutine-Task Labor (1990)*. Monthly employment is aggregated from the number of individuals in an occupation, weighted by the CPS sampling weights, and seasonally adjusted using Census X12 ARIMA. The series are further logged and band-pass filtered to remove fluctuations at frequencies higher than 18 months. The shaded areas indicate NBER recession months. This figure shows a pattern consistent with that in Jaimovich and Siu (2014), who classify routine-task labor based on broad occupation groups. (Color figure can be viewed at wileyonlinelibrary.com)

be a major factor in hiring routine- versus nonroutine-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.

A salient feature of routine-task jobs that is crucial to this paper is that these jobs tend to be lost in recessions but not in expansions (Jaimovich and Siu (2014)). I therefore examine the employment of routine-task labor (defined consistent with my proposed methodology) over the business cycle. Figure 1 illustrates a similar pattern as in Jaimovich and Siu (2014): while the employment of routine-task labor declines during recessions, it does not tend to bounce back during recovery periods in the same way as the employment of nonroutine-task labor. These observations are consistent with my model's prediction that firms replace routine-task labor with machines in the face of unfavorable aggregate shocks, which I test in depth in the next section.

III. Empirical Evidence

In this section, I present empirical evidence to support the model's implications for (1) the relation between *RShare* and firms' other characteristics, (2) the relation between *RShare* and firms' systematic risk in the cross-section, and (3) the mechanism for high-*RShare* firms' low systematic risk due to countercyclical labor-technology substitution. I elaborate the goals of each test in the subsections below.

A. RShare and Firm Characteristics

I start by summarizing firms' *RShare*. Panel A of Table II 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 category into five portfolios based on their *RShare*. Throughout this paper, I use within-industry sorting to mitigate the concern that different industries' production technologies may require different intensities of routine-task input relative to nonroutine-task input in practice, which is outside the scope of my model.

Panel B of Table II shows that high-*RShare* firms have lower stocks of machinery and equipment relative to their total physical capital and to their structural capital. This is consistent with the view that high-*RShare* firms have not replaced their routine-task labor with machines to the same extent as low-*RShare* firms. In addition, consistent with the model prediction that firms maintain a high *RShare* because they have not experienced negative shocks to cash flows, I find that high-*RShare* firms have much higher cash flows than low-*RShare* firms.

I next examine the relation between firms' *RShare* and their operating costs and operating leverage based on Novy-Marx (2011). Carlson, Fisher, and Giammarino (2004) argue that, in theory, a firm's book-to-market ratio proxies for its operating leverage. I therefore calculate firms' book-to-market ratio as an alternative proxy for their operating leverage. I find that high-*RShare* firms have higher operating costs, higher operating leverage, and higher book-to-market than low-*RShare* firms. These results are consistent with my model's prediction that high-*RShare* firms are more "geared up" in production than low-*RShare* firms because routine-task labor incurs higher production cost than machines.

I further examine the relation between *RShare* and growth opportunities and financial leverage, which are not captured in my model. Carlson, Fisher,

Table II

Summary Statistics

This table presents 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 for its routine-task labor to its total wage expense, as defined in equation (19). *Sector* is at the one-digit SIC industry sector level. Panel B reports characteristics of firms sorted into five portfolios based on their *RShare* within-industry. Each year, firms in each Fama-French 17 industry 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 and administrative expense (SG&A) normalized by firms' total assets. *Op. Lev* is firms' operating leverage measured by the sum of COGS and SG&A divided by firms' 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 detailed variable definitions.

Panel A: Firm *RShare* by Sectors

Sector	Agriculture	Mining	Construction	Manufacturing	Transportation	Wholesale	Retail	Finance	Service	Administration	Total
Mean	0.14	0.12	0.07	0.18	0.09	0.16	0.24	0.14	0.11	0.13	0.15
SD	0.15	0.15	0.09	0.17	0.11	0.14	0.18	0.15	0.14	0.15	0.16
N	272	3,946	1,202	44,271	11,303	3,974	8,258	13,929	19,406	877	107,438

Panel B: Firm Characteristics in Portfolios Sorted on *RShare*

Quint.	*RShare*	*Mach/Capital*	*Mach/Struct*	*Cash Flow*	*Op. Cost*	*Op. Lev*	*B/M*	*Size*	*Mkt. Lev*
L	0.02	0.64	6.86	−0.82	1.07	1.57	0.59	12.53	0.15
2	0.07	0.63	5.23	−0.06	1.08	1.72	0.62	12.85	0.18
3	0.12	0.63	4.73	0.12	1.11	1.94	0.66	12.88	0.20
4	0.20	0.62	4.37	0.31	1.18	2.01	0.66	12.98	0.21
H	0.38	0.61	4.18	0.28	1.28	2.22	0.69	12.67	0.21

and Giammarino (2004) suggest that a firm's growth opportunities can be proxied by the firm's size. Hence, I examine firm size in the five portfolios above. I do not find a relation between firms' *RShare* and their size, indicating that high-*RShare* firms and low-*RShare* firms have similar growth opportunities in general. Interestingly, high-*RShare* firms have slightly higher financial leverage than low-*RShare* firms.

B. 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 have higher operating leverage, which mitigates the effect of switching options (see equation (16)). Tests that control for operating leverage therefore 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.

B.1. Portfolio Returns

I use portfolio analysis to explore the relation between firms' share of routine-task labor and their stock returns. Specifically, at the end of each June, firms in each Fama-French 17 industry are sorted into five value-weighted portfolios based on their *RShare*. By construction, *RShare* increases from 0.02 for the lowest quintile portfolio to 0.39 for the highest quintile portfolio (see Table II). In Panel A of Table III, I find that excess returns monotonically decrease from 10.19% for the lowest *RShare* quintile to 6.28% for the highest *RShare* quintile, yielding an average return spread of −3.9% per year, which is statistically significant.

This return spread is the same order of magnitude as those for risk factors commonly used in the finance literature. For instance, in Panel B, we see that the time series average of the size factor, value factor, profitability factor, and investment factor of Fama and French (2015) ranges from 2.26% to 3.95% during my sample period.

I next check the robustness of the above results to financial leverage. I calculate firms' unlevered stock returns following Liu, Whited, and Zhang (2009) and conduct the portfolio analysis using excess unlevered returns. The unlevered stock returns are calculated as

$$R^{Unlev}_{f,m,y} = (1 - w_{f,y-1})R^{Raw}_{f,m,y} + w_{f,y-1}R^{Bond}_{f,m,y}(1 - Tax_y), \tag{20}$$

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 in year y, and $w_{f,y-1}$ is the market leverage ratio of firm f at the end of year $y - 1$.[14]

[14] 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

Table III

Five Portfolios Sorted on *RShare*

Panel A reports the time series averages of stock returns for five portfolios sorted on the share of routine-task labor (*RShare*) within-industry (see notes to Table II). At the end of each June, firms in each Fama-French 17 industry are sorted into five value-weighted portfolios based on their *RShare*. *Excess Returns* are monthly returns minus the one-month Treasury bill rate. *Unlevered Returns* are monthly unlevered returns, defined as in equation (20) following Liu, Whited, and Zhang (2009), minus the one-month Treasury bill rate. The sample covers stock returns from July 1992 to June 2016. Table B reports time series averages of annual returns of the market (*Mkt-Rf*), size (*SMB*), value (*HML*), profitability (*RMW*), and investment (*CMA*) factors of Fama and French (2015) from July 1992 to June 2016. Data on factors are downloaded from Ken French's website. In all statistics, Newey-West standard errors (Newey and West (1987)) are estimated with four lags and reported in parentheses. All returns and their standard errors are annualized by multiplying by 12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Annual Portfolios Returns					
L	2	3	4	H	H − L
Mean excess returns					
10.19**	9.72**	9.24***	8.42***	6.28**	−3.91*
(3.95)	(3.89)	(3.43)	(2.96)	(3.04)	(2.21)
Mean unlevered returns					
9.23**	8.82**	8.59***	7.31***	5.49**	−3.74*
(3.64)	(3.58)	(3.07)	(2.62)	(2.69)	(2.07)

Panel B: Annual Factor Returns				
Mkt-Rf	*SMB*	*HML*	*RMW*	*CMA*
7.57**	2.26	2.65	3.95*	3.38**
(3.25)	(2.02)	(2.48)	(2.25)	(1.62)

Panel A of Table III reports the results of excess unlevered returns for firms in five *RShare* portfolios sorted within industry. We observe results very similar to those for excess returns in terms of monotonicity and significance of the spread, suggesting that financial leverage is unlikely to be driving the portfolio results.

A common caveat in using future realized returns to proxy for expected returns is that the proxy is accurate only when the sample period is long enough to cover all economic states. For a sample of 25 years, my proxy for expected returns may be subject to noise. Hence, in the rest of the analyses, I focus primarily on the relation between *RShare* and firms' exposure to systematic risk.

B.2. Betas

In this section, I explore the relation between firms' *RShare* and their exposure to systematic risk. My first set of proxies for this exposure comprises the

rating category. I adopt the same method by using the Barclays U.S. aggregate monthly bond return series from the Morningstar database for five credit rating categories: Aaa, Aa, A, Baa, and high yield.

Table IV
CAPM Betas and *RShare*

This table reports the unconditional CAPM time series regression results in the top panel and the conditional CAPM regression results (Lewellen and Nagel (2006)) in the bottom panel 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 value-weighted portfolios based on their *RShare*. Newey-West (1987) standard errors, reported in parentheses, are estimated with four lags for the unconditional CAPM monthly estimations and with one lag for the conditional CAPM yearly estimation. CAPM alphas in the top panel, average CAPM alphas in the bottom panel, as well as their standard errors are annualized by multiplying by 12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample covers stock returns from July 1992 to June 2016.

	L	2	3	4	H	H − L
			Unconditional CAPM			
MKT β	1.10***	1.09***	1.02***	0.87***	0.86***	−0.23***
	(0.05)	(0.03)	(0.03)	(0.02)	(0.04)	(0.06)
α (%)	1.88	1.41	1.52	1.80*	−0.26	−2.15
	(1.79)	(1.63)	(1.08)	(1.01)	(1.29)	(2.10)
R^2	0.77	0.86	0.86	0.87	0.81	0.18
			Conditional CAPM			
Avg. MKT β	1.07***	1.00***	1.02***	0.87***	0.85***	−0.22***
	(0.05)	(0.08)	(0.07)	(0.04)	(0.04)	(0.05)
Avg. α (%)	1.48	1.77	0.82	0.30	−0.62	−2.14
	(1.52)	(1.44)	(1.16)	(0.82)	(1.05)	(1.66)
Avg. R^2	0.77	0.87	0.87	0.86	0.84	0.25

market betas under the unconditional and the conditional CAPM frameworks. Estimation of the unconditional CAPM betas assumes that betas are constant over time, while estimation of the conditional CAPM betas relaxes this assumption. I estimate market betas under the conditional CAPM for the five portfolios above following the methodology described in Lewellen and Nagel (2006) using monthly returns within yearly windows.

Table IV shows that the market betas estimated under both the unconditional and the conditional CAPM decrease 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 an average conditional market beta of −0.22, both of which are highly significant. The point estimates of alphas for the long-short portfolio are −2.15% and −2.14% under the unconditional and conditional CAPM frameworks, respectively. However, neither is statistically different from zero.

One shortcoming of examining only the market betas is that the market portfolio returns can reflect systematic risk sourced from both aggregate cash flow news and aggregate discount rate news (Campbell and Vuolteenaho (2004)). However, in my model, systematic risk derives solely from aggregate cash flow shocks. Hence, I examine a second set of proxies for systematic risk. Another advantage of testing these alternative proxies is that I can capture additional

Table V

Alternative Measures of Systematic Risk and *RShare*

Panel A shows the cash flow betas for five portfolios sorted on share of routine-task labor based on the decomposition of the CAPM betas. At the end of each June, firms in each Fama-French 17 industry are sorted into five value-weighted portfolios based on their *RShare*. β_{CF} and β_{DR} are the portfolios' beta to aggregate cash flow news (cash flow beta) and beta to aggregate discount rate news, respectively, constructed following Campbell and Vuolteenaho (2004). β is the sum of the two betas. Panel B shows the results of regressing annualized quarterly excess returns of the portfolios on the annualized quarterly growth rate of real GDP. The intercepts are not reported for brevity. Newey-West (1987) standard errors are estimated with one lag and reported in parentheses. Quarterly excess returns and their standard errors are annualized by multiplying by four and are reported in percentages. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample covers stock returns from July 1992 to June 2016.

Panel A: Cash Flow Beta from Beta Decomposition

	L	2	3	4	H	H–L
β_{CF}	0.60***	0.55***	0.54***	0.46***	0.45***	−0.14***
	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.05)
β_{DR}	0.56***	0.59***	0.49***	0.44***	0.46***	−0.10**
	(0.08)	(0.09)	(0.07)	(0.07)	(0.06)	(0.04)
β	1.16***	1.14***	1.04***	0.90***	0.91***	−0.24***
	(0.11)	(0.11)	(0.09)	(0.08)	(0.08)	(0.08)

Panel B: Beta to Quarterly GDP Shocks

	L	2	3	4	H	H − L
β_{GDP}	5.07***	4.87***	4.16***	3.78***	3.48***	−1.59*
	(1.30)	(1.34)	(1.12)	(0.85)	(0.79)	(0.92)
$E[R] - r_f$ (%)	10.41**	9.91**	9.43***	8.55***	6.41**	−4.00*
	(4.11)	(4.10)	(3.55)	(3.13)	(3.21)	(2.21)

systematic risk that is not reflected by the market portfolio. To the extent that the systematic risk that really matters to investors may not be fully captured by beta, examining multiple proxies for systematic risk is a valuable exercise.

In Panel A of Table V, I decompose the CAPM beta for each portfolio into cash flow beta and discount rate beta, following Campbell and Vuolteenaho (2004). The table shows that cash flow beta monotonically decreases with *RShare*, resulting in a significant negative spread of 0.14 for the long-short portfolio. In addition, cash flow beta accounts for over 60% (0.14/0.24) of the CAPM beta of the long-short portfolio. The significant presence of cash flow beta in the CAPM beta also helps explain why the expected returns of my portfolios and their CAPM betas seem to align (see Campbell and Vuolteenaho (2004) and Weber (2015)).

In Panel B of Table V, I directly measure the sensitivity of the portfolios' quarterly excess returns to the quarterly growth rate of real GDP, which is a proxy for shocks to aggregate cash flows. We again observe that firms with higher *RShare* exhibit lower exposure to aggregate cash flow shocks.

In summary, these results support my model's core prediction that firms with higher *RShare* have lower exposure to systematic risk.

B.3. Double Sorting

I next perform conditional double sorting of portfolios to achieve two goals. First, the double sorting helps test the additional model prediction that, conditional on operating leverage, *RShare* should convey an even stronger signal for firms' hedging options (see equation (16)). Hence, we expect to see a larger beta for the long-short portfolio sorted on *RShare* after controlling for operating leverage. Second, the double sorting provides a robustness check to the one-way-sorted analyses by allowing for a nonparametric association between firms' other characteristics and their systematic risk.

To do so, I first sort firms in each industry into three bins based on a firm characteristic. Within each bin, I further sort firms into five value-weighted portfolios based on their *RShare*, resulting in 15 portfolios in total. For each category of *RShare* (i.e., L, 2, 3, 4, H), I report the average CAPM beta across sorts of the firm characteristic in Table VI.

The second row of Table VI shows that after controlling for operating leverage, high-*RShare* firms have a much lower beta than low-*RShare* firms, with the beta for the long-short portfolio equal to -0.33. The larger economic magnitude of this spread compared to the spread of beta based on the unconditional sorting, -0.23, supports the model prediction that controlling for operating leverage enhances the negative relation between *RShare* and firms' exposure to systematic risk. The third row uses the book-to-market ratio as an alternative proxy for operating leverage, which also yields some enhancement of beta for the long-short portfolio. The fourth and seventh rows further show that the relation between *RShare* and beta is robust to controlling for firms' operating costs, cash flows, size, and market leverage.

B.4. Panel Regressions

In this section, I examine the robustness of the relation between firms' *RShare* and their exposure to systematic risk by controlling for other firm characteristics in panel regressions. Specifically, I use the specification

$$\begin{aligned} \beta^{Cond}_{f,t} &= b_0 + b_1 RShare_{f,t-1} + b_2 Char_{f,t-1} + F_{Ind\times Year} + \epsilon_{f,t} \\ R_{f,t} - RF_t &= b_0 + b_1 RShare_{f,t-1} + b_2 Char_{f,t-1} + F_{Ind\times Year} + \epsilon_{f,t}, \end{aligned} \tag{21}$$

where $\beta^{Cond}_{f,t}$ is the conditional beta of firm f in year t constructed using 12 monthly stock returns following Lewellen and Nagel (2006), $R_{f,t} - RF_t$ is the annual excess return of firm f in year t, $RShare_{f,t-1}$ is the share of routine-task labor of firm f in year $t-1$, $Char_{f,t-1}$ denotes the other firm characteristics in year $t-1$, and $F_{Ind\times Year}$ denotes industry-year fixed effects. I double cluster standard errors at the firm and year levels.

Table VI

Betas of Double-Sorted Portfolios

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 one of the firms' characteristics. Within each bin, I further sort firms into five value-weighted portfolios based their *RShare*, resulting in 15 portfolios in total. For each category of *RShare* (i.e., L, 2, 3, 4, H), I report average excess returns across the sorts of the firms' characteristics. See Appendix B for definitions of firm characteristics. Newey-West (1987) standard errors are estimated with four lags and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample covers stock returns from July 1992 to June 2016.

	L	2	3	4	H	H − L
			Unconditional sorting			
MKT β	1.10***	1.09***	1.02***	0.87***	0.86***	−0.23***
	(0.05)	(0.03)	(0.03)	(0.02)	(0.04)	(0.06)
			Conditional on operating leverage			
MKT β	1.14***	1.05***	1.00***	0.91***	0.81***	−0.33***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)
			Conditional on book-to-market ratio			
MKT β	1.16***	1.06***	0.97***	0.89***	0.90***	−0.26***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)
			Conditional on operating cost			
MKT β	1.12***	1.06***	0.97***	0.89***	0.91***	−0.22***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.05)
			Conditional on cash flows			
MKT β	1.12***	1.10***	1.06***	0.98***	0.93***	−0.18***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)
			Conditional on size			
MKT β	1.23***	1.14***	1.11***	1.02***	1.02***	−0.22***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
			Conditional on market leverage			
MKT β	1.14***	1.00***	1.02***	0.92***	0.92***	−0.22***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)

Table VII reports the results. Two observations stand out. First, *RShare* persistently negatively predicts conditional betas (in Panel A) and future annual excess returns (in Panel B) with and without controlling for operating leverage, book-to-market ratio, operating costs, cash flows, size, and market leverage. A one-standard-deviation increase in *RShare* (16% in Table II) is associated with a reduction in a firm's exposure to systematic risk by 0.09 to 0.10, and future annual returns by 1% to 1.64%. Second, consistent with the model's prediction, *RShare* more strongly predicts conditional betas and future returns when controlling for operating leverage. For instance, the magnitude of the coefficient on *RShare* in Panel B increases dramatically by 59% (from −6.48 to −10.28) when controlling for operating leverage.

Table VII

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

This table reports the predictability of firms' share of routine-task labor (*RShare*) on their conditional betas and annual excess stock returns, while controlling for known firm characteristics that predict risk. Conditional betas are calculated following Lewellen and Nagel (2006) for each year t. Annual excess stock returns are in percentages. See Appendix B for definitions of firm characteristics. All regressions include fixed effects of industry interacted with year, where I use the 17-industry classification of Fama and French (1997). Standard errors are clustered at both the firm and year levels and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Conditional Betas								
$RShare_{t-1}$	−0.59***	−0.61***	−0.59***	−0.58***	−0.55***	−0.61***	−0.62***	−0.54***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.14)
$Op.Lev_{t-1}$		0.02						0.02
		(0.01)						(0.01)
B/M_{t-1}			0.01					−0.12**
			(0.05)					(0.05)
$Op.Cost_{t-1}$				−0.03				−0.12***
				(0.04)				(0.04)
$Cash\ Flow_{t-1}$					−0.03***			−0.02***
					(0.01)			(0.01)
$Size_{t-1}$						−0.08***		−0.09***
						(0.02)		(0.03)
$Mkt.Lev_{t-1}$							0.28	0.17
							(0.18)	(0.16)
Observations	40,416	40,416	40,416	40,416	40,416	40,416	40,416	40,416
Adjusted-R^2	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Panel B: Annual Stock Returns								
$RShare_{t-1}$	−6.48*	−10.28***	−9.14**	−7.83**	−6.47*	−6.22*	−6.75**	−9.00***
	(3.46)	(3.76)	(3.61)	(3.44)	(3.33)	(3.50)	(3.32)	(3.25)
$Op.Lev_{t-1}$		2.93***						4.23***
		(0.71)						(1.07)
B/M_{t-1}			7.97***					8.19***
			(1.78)					(1.41)
$Op.Cost_{t-1}$				3.23***				−3.08
				(0.85)				(2.24)
$Cash\ Flow_{t-1}$					−0.01			−0.23
					(0.27)			(0.24)
$Size_{t-1}$						1.41**		3.97***
						(0.59)		(0.43)
$Mkt.Lev_{t-1}$							2.81	−3.57***
							(5.94)	(0.75)
Observations	40,416	40,416	40,416	40,416	40,416	40,416	40,416	40,416
Adjusted-R^2	0.13	0.14	0.13	0.13	0.13	0.13	0.13	0.15

C. Inspecting the Mechanism

The main mechanism of my model is that firms with higher *RShare* can save value through cost-saving labor-technology substitution in response to unfavorable aggregate shocks. I evaluate the validity of this mechanism using four tests. Specifically, in response to unfavorable aggregate shocks, firms with higher *RShare* should (i) invest more in technology, (ii) lay off more routine-task labor, (iii) cut operating costs more, and (iv) experience less of a decline in firm value. Due to the model's strict focus on the cross-sectional heterogeneity of firms, I focus on high-*RShare* firms and use their industry peers with a low *RShare* as a counterfactual in all upcoming tests. The differential responses to aggregate shocks between high-*RShare* and low-*RShare* firms identify the model mechanism.

C.1. Investment in Technology and Aggregate Shocks

Here, I compare the investment responses of firms with different *RShare* to unfavorable aggregate shocks. Investment in machines is measured by the real growth rate of machinery and equipment at cost (Compustat item FATE). The advantage of using the "at cost" measure is that it is recorded before amortization and depreciation. Hence, year-over-year changes in this variable are better indicators of firms' investment in machines. I employ the growth rate of real GDP as a proxy for aggregate shocks. I use the following specification:

$$I^M_{f,t} = a_0 + \sum_{d=2}^{5} a_d D(R_{f,t-1})_d + b_1 Shock_t + \sum_{d=2}^{5} b_d D(R_{f,t-1})_d \times Shock_t + cX_{f,t-1} + F_f + \epsilon_{f,t}, \tag{22}$$

where $I^M_{f,t}$ is firm f's investment in machines in year t, $Shock_t$ is the GDP shock in year t, and $D(R_{f,t-1})_d$ is a dummy variable indicating whether the firm's *RShare* belongs to quintile d in year $t-1$.[15] $X_{f,t-1}$ represents other firm characteristics known to predict investment (including the logarithm of Tobin's Q, market leverage, cash flows, cash holdings, total assets), and F_f represents firm fixed effects.

I focus on the coefficients on the interaction terms ($b_2, \ldots, b_5$), which measure differences in the response of investment to aggregate shocks. I present the main results in the first two columns of Table VIII and a placebo test (which I will discuss later in Section III.C.6) in columns (3) and (4). The first column shows that a one-standard-deviation decrease in real GDP growth rate (1.7% during my sample period) is associated with a 1.5% (0.86 × 1.7%) decrease in investment in machines, on average. The second column shows the main result, namely, how this investment response varies with the firm's *RShare*. A one-standard-deviation decrease in real GDP growth rate reduces investment in

[15] The quintile breakpoints vary by industry. I use the 17-industry classifications of Fama and French (1997).

Table VIII

Response of Firm Technology Investment to Aggregate Shocks

This table shows the mechanism of labor-technology substitution by reporting the response of investment to aggregate shocks for firms with different shares of routine-task labor, *RShare*. The sample period is 1990 to 2014. Investment in *Machines* is the real growth rate of machinery and equipment capital from $t-1$ to t. Investment in *Other Capital* is the real growth rate of property, plant, and equipment excluding machinery and equipment from $t-1$ to t. Investment in *Computers* is the growth rate of the number of computers in firms' establishments from $t-1$ to t based on the CiTDB data. *Shock* is the growth rate of real GDP from $t-1$ to t. $D(R)_d$ is a dummy quintile variable equal to 1 if the firm's *RShare* belongs in quintile d at year $t-1$. The breakpoints for the quintile sorting vary by industry. I use the 17-industry classification of Fama and French (1997). All regressions include a vector of controls of firm fixed effects and lagged values of log Tobin's Q, market leverage, cash flows, cash holdings, and log total assets. See Appendix B for variable definitions. Coefficients of quintile dummies and firm controls are not reported for brevity. Establishment-level regressions in columns (5) and (6) are weighted by the establishments' number of computers within firm at $t-1$. All standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Compustat Firms				CiTDB Establishments	
	Machines		Other Capital		Computers	
Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.86***	1.40***	0.99***	1.21**	0.41***	1.04***
	(0.10)	(0.27)	(0.17)	(0.52)	(0.10)	(0.23)
$D(R)_2 \times$ *Shock*		−0.49		−0.06		−0.67**
		(0.34)		(0.64)		(0.31)
$D(R)_3 \times$ *Shock*		−0.63*		−0.08		−0.69**
		(0.33)		(0.61)		(0.30)
$D(R)_4 \times$ *Shock*		−0.65**		−0.37		−0.77**
		(0.33)		(0.61)		(0.30)
$D(R)_5 \times$ *Shock*		−0.80***		−0.48		−0.94***
		(0.29)		(0.60)		(0.31)
Observations	41,601	41,601	40,403	40,403	1,405,940	1,405,940
Adjusted-R^2	0.21	0.21	0.14	0.14	0.07	0.07

machines by 2.4% for firms in the lowest *RShare* quintile group but only 1% for firms in the highest *RShare* quintile group. The differential response between the two groups, −1.4%, is statistically significant and economically sizable (e.g, the sample mean of firms' machinery investment rate is 10.32%).

To show the magnitude of the differential investment responses to *negative* aggregate shocks, in Figure 2 I plot the investment rate in machines for high-*RShare* and low-*RShare* firms before and after recessions. In the years before the 2001 and 2008 to 2009 recessions, I categorize firms into high-*RShare* and low-*RShare* groups based on the median *RShare* within-industry. I track the average investment rate in machines of these two groups in six-year windows around the 2001 recession in Panel A and the 2008 to 2009 recession in Panel B. Both panels show that recessions reduce investment in machines much more in low-*RShare* firms than in high-*RShare* firms. The difference of investment

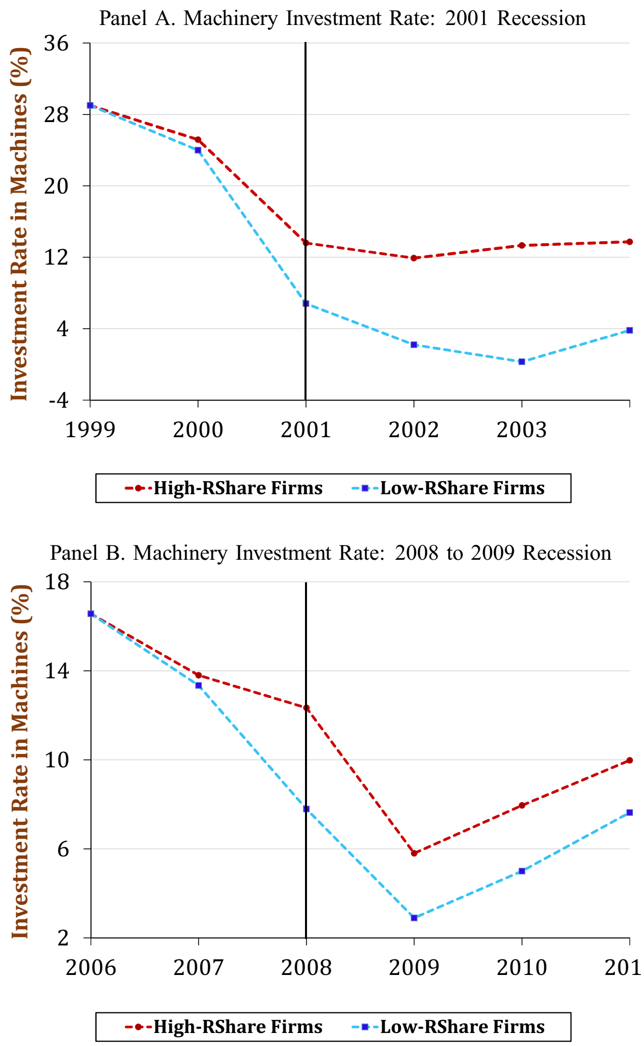

Figure 2. Investment in machines around recessions by high- *RShare* and low- *RShare* firms within industry. This figure plots the average rate of investment in machines over time for firms sorted according to their share of routine-task labor (*RShare*) within-industry. The rate of investment in machines is defined as the growth rate of machinery and equipment at cost from $t-1$ to t. Firms' *RShare* is defined in equation (19). In the years before the recessions, firms in each Fama-French 17 industry are sorted into high-*RShare* and low-*RShare* groups based on whether their *RShare* is above or below the industry's median *RShare* value. The treatment years are 2001 through 2004 for the 2001 recession and 2008 through 2011 for the 2008 to 2009 recession. In these years, the difference between the dark red lines and the light blue lines provides a difference-in-differences estimator for the effect of negative aggregate shock for those groups. The earlier years provide placebo tests. To align the first year of each series and ease comparison of trends, I subtract from each dot the group mean in the first year and add back the pooled mean from the first year. The first-year machinery investment rate is 23.9% for high-*RShare* firms and 34.1% for low-*RShare* firms in Panel A, and 14.7% and 18.4%, respectively, in Panel B. (Color figure can be viewed at wileyonlinelibrary.com)

rate between the two groups ranges from 6.8% to 13% during and after the 2001 recession and from 2.9% to 4.6% during and after the 2008 to 2009 recession. In Section III.C.5, I further confirm the robustness of this pattern around recessions by including controls in the regressions.

To provide even more direct evidence of firms' investment in technology, I also examine firms' investment in computers. Since direct measures of firm investment in automation are scarce and some machines may have nothing to do with job replacement, firms' adoption of computers at work sites has been closely tied to RBTCs. Indeed, the classification of occupations into routine and nonroutine is intended to shed light on how technology, especially computerization, alters job skill demands (see the seminal paper by Autor, Levy, and Murnane (2003)).

I measure computer investment as the growth in the number of computers in establishments of Compustat firms.[16] In particular, I use equation (22) and weight the regressions by establishments' lagged number of computers within each firm-year. Column (5) of Table VIII shows that computer investment, on average, has lower cyclicality than machinery investment. Column (6) shows more substantial differences in firms' response to aggregate shocks. Most prominently, computer investment of firms in the highest *RShare* quintile group is noncyclical: a one-standard-deviation change in real GDP growth is associated with only a 0.17% change in computer investment for these firms. These enhanced results compared to those for investment in machines reinforce the view that in bad times, high-*RShare* firms are more likely to invest in technology than low-*RShare* firms.

C.2. Employment of Routine-Task Labor and Aggregate Shocks

In this section, I show that high-*RShare* firms reduce routine-task labor more than low-*RShare* firms in the face of unfavorable aggregate shocks.

The OES microdata cover each establishment for every three years. Therefore, I examine firms' response to GDP shocks over the three-year horizon at the establishment level, and I weight establishments in the regressions within each firm-year. Specifically, I measure the growth rate of establishments' routine-task employment as the three-year difference in routine-task employment divided by the average of routine-task employment in years $t-3$ and t.[17] I use the average of routine-task employment in the establishment in

[16] Establishment-level data on the number of computers are from the Computer Intelligence Technology Database (CiTDB). CiTDB is a private-sourced database that has been frequently used to measure the impact of IT investments in the management and information systems literatures (see Bresnahan, Brynjolfsson, and Hitt (2002), Brynjolfsson and Hitt (2003), and Bloom, Sadun, and Van Reenen (2012), among others). See Appendix B for more details on the data.

[17] That is, $g = 2(x_t - x_{t-3})/(x_t + x_{t-3})$. Davis et al. (2014, p. 3967) 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." Exit and entry of routine-task labor exists for establishments in my sample, but are not sizable. Using alternative measures, such as the percentage growth rate, leads to a smaller sample size but similar results.

years $t-3$ and t as weight in the following regression specification:

$$Chg_{e,t-3,t} = a_0 + \sum_{d=2}^{5} a_d D(R_{f,t-3})_d + b_1 Shock_{t-3,t} + \sum_{d=2}^{5} b_d D(R_{f,t-3})_d \times Shock_{t-3,t} + F_f + \epsilon_{e,t}, \tag{23}$$

where $Chg_{e,t-3,t}$ is the growth rate of routine-task employment in establishment e from year $t-3$ to year t, $Shock_{t-3,t}$ is the growth in real GDP from $t-3$ to t, and $D(R_{f,t-3})_d$ is a dummy variable indicating whether the firm's *RShare* belongs to quintile d in year $t-3$. The quintile breakpoints vary by industry, where I use the 17-industry classification of Fama and French (1997). Finally, F_f represents firm fixed effects.

Column (1) of Panel A in Table IX shows that firms' employment of routine-task labor is highly cyclical. A one-standard-deviation decrease in three-year real GDP growth (about 4% during my sample period) is associated with roughly a 5% (4% $\times$ 1.34) reduction in routine-task employment for an average firm. Column (2) shows that such a reduction in routine-task employment is much more pronounced in high-*RShare* firms (roughly a 7% reduction) than in low-*RShare* firms (an insignificant 1% increase).

C.3. Labor-Technology Substitution and Aggregate Shocks

One caveat in testing firms' investment and employment policies separately is that these findings may be driven by different subsets of firms. In other words, in response to unfavorable aggregate shocks, some high-*RShare* firms may invest more in machines, and other high-*RShare* firms may reduce routine-task labor more, with these two sets of high-*RShare* firms not overlapping. Therefore, the results that we see in the previous sections may not be sufficient to show that high-*RShare* firms are *substituting* their routine-task labor with machines. To eliminate this possibility and support the substitution hypothesis, I investigate the sensitivity of a firm's routine-task employment to its machinery investment (i.e., its "degree of substitution"). Specifically, I examine the response of this degree of substitution to aggregate shocks for high-*RShare* firms and low-*RShare* firms using the following regression specification:

$$\begin{aligned} Chg_{e,t-3,t} = a_0 + a_1 I^M_{t-3,t} &+ \sum_{d=2}^{5} a_d D(R_{f,t-3})_d \times I^M_{t-3,t} \\ &+ \sum_{d=2}^{5} b_d D(R_{f,t-3})_d \times Shock_{t-3,t} \times I^M_{t-3,t} \\ &+ \sum_{d=2}^{5} c_d D(R_{f,t-3})_d \times Shock_{t-3,t} + c_1 Shock_{t-3,t} \\ &+ \sum_{d=2}^{5} g_d D(R_{f,t-3})_d + F_f + \epsilon_{e,t}, \end{aligned} \tag{24}$$

Table IX

Response of Firm Routine-Task Employment to Aggregate Shocks

Panel A shows the mechanism of labor-technology substitution by reporting the response of routine-task employment to aggregate shocks at the establishment level. Change in *Routine Employment* is an establishment's three-year change in employment of routine-task labor normalized by the average of the establishment's routine-task employment in years $t-3$ and t. Change in *Share of Routine Employment* is the change in the ratio of establishments' routine-task employment and total employment from $t-3$ to t. Change in *Share of Routine Wage Bill* is defined similarly using the ratio of total wages paid to routine-task labor and the establishment's total wage expense. In all variable constructions, routine-task labor is defined in $t-3$ and maintains the same definition for three years to form the time-series changes in the dependent variables. This procedure restricts the sample to the period 1996 to 1998 and 2002 to 2014 in columns (1) to (4) and 2002 to 2014 in columns (5) and (6) since wage data are available in the microdata after 1998 (see Appendix B for more details). *Shock* is the growth rate of real GDP from $t-3$ to t. $D(R)_d$ is a dummy quintile variable equal to 1 if the firm's *RShare* belongs in quintile d at year $t-3$. The breakpoints for the quintile sorting vary by industry. I use the 17-industry classification of Fama and French (1997). Coefficients of quintile dummies are not reported for brevity. Panel B shows how the sensitivity of firms' routine-task employment to investment responds to aggregate shocks. I is firms' three-year investment rate in machines in columns (1) and (2) and three-year investment rate in other capital in columns (3) and (4). Coefficients on quintile dummies and interaction terms related to $D(R)_2$ and $D(R)_3$ are not reported for brevity. All regressions include firm fixed effects. I weight establishments within each firm-year for all regressions. The weights are the average of the establishments' routine-task employment in $t-3$ and t when the dependent variable is routine employment, and the average of total employment (total real wages) in $t-3$ and t when the dependent variable is the share of routine employment (share of routine wages). All standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Routine-Task Employment

	Routine Emp.		Share of Routine Emp.		Share of Routine Wage Bill	
Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
Shock	1.34***	−0.25	0.09***	−0.11**	0.06**	−0.07
	(0.15)	(0.43)	(0.03)	(0.06)	(0.03)	(0.05)
$D(R)_2 \times$ *Shock*		1.44***		0.12		0.06
		(0.55)		(0.08)		(0.07)
$D(R)_3 \times$ *Shock*		1.81***		0.19**		0.19***
		(0.52)		(0.08)		(0.07)
$D(R)_4 \times$ *Shock*		1.65***		0.18**		0.11
		(0.52)		(0.09)		(0.08)
$D(R)_5 \times$ *Shock*		1.98***		0.35***		0.29***
		(0.51)		(0.10)		(0.09)
# Firm-Year	38,056	38,056	38,056	38,056	35,356	35,356
Observations	146,551	146,551	164,889	164,889	157,907	157,907
Adjusted-R^2	0.08	0.12	0.07	0.12	0.07	0.12

(Continued)

Table IX—*Continued*

Panel B: Sensitivity of Routine-Task Employment to Investment				
	Routine Empl.			
	I = Machines		I = Other Capital	
Dep. Var.	(1)	(2)	(3)	(4)
I	0.01	0.07*	0.03***	−0.04
	(0.01)	(0.04)	(0.01)	(0.04)
...				
$I \times D(R)_4$	−0.01	−0.10*	0.05	0.06
	(0.02)	(0.05)	(0.03)	(0.07)
$I \times D(R)_5$	0.01	−0.08*	−0.02*	0.06
	(0.02)	(0.05)	(0.01)	(0.04)
...				
$I \times D(R)_4 \times Shock$		0.88*		−0.16
		(0.49)		(0.77)
$I \times D(R)_5 \times Shock$		1.10**		−1.04*
		(0.50)		(0.53)
...				
$D(R)_4 \times Shock$		0.85		0.95
		(0.94)		(0.97)
$D(R)_5 \times Shock$		1.30		1.72*
		(0.92)		(0.95)
$I \times Shock$		−0.64		0.89*
		(0.40)		(0.51)
$Shock$		0.02		−0.44
		(0.78)		(0.82)
Observations	66,785	66,785	66,392	66,392
Adjusted-R^2	0.14	0.14	0.14	0.14

where $I^{M}_{t-3,t}$ is firm f's three-year real investment rate in machines and the other variables are as defined in equation (23).

The coefficients $a_1, \ldots, a_5$ can be interpreted as the differential degree of substitution between high-*RShare* and low-*RShare* firms when three-year real GDP growth is zero (which is a state of low economic growth, since the average three-year real GDP growth is 6.7% in my sample). I focus on the coefficients $b_2, \ldots, b_5$ on the triple interaction terms, which can be interpreted as the differential responses of the degree of substitution to aggregate shocks for high-*RShare* and low-*RShare* firms. Finally, the coefficients $c_1, \ldots, c_5$ capture the differential response of routine-task employment to aggregate shocks for high-*RShare* and low-*RShare* firms, conditional on the firms not investing in machines.

Column (1) of Panel B in Table IX shows that high-*RShare* and low-*RShare* firms do not differ in their degree of substitution in an average year. Column (2) shows the main finding that in a low economic state when three-year GDP growth is zero, high-*RShare* firms exhibit a stronger degree of substitution than low-*RShare* firms, as indicated by the coefficients $a_4 = -0.1$ and $a_5 = -0.08$, which are both significantly different from zero. More importantly, we find that when GDP growth drops further, such differential response in the degree of substitution increases, as $b_4 = 0.88$ and $b_5 = 1.10$, with both of these coefficients significantly different from zero. Finally, when we condition on not investing in machines, we observe no differential responses of routine-task employment to aggregate shocks between high-*RShare* and low-*RShare* firms. This result suggests that the differential employment response to aggregate shocks is fueled by stronger technology investment in high-*RShare* firms.

In summary, the two findings on investment and employment show that an average high-*RShare* firm responds to unfavorable aggregate shocks by increasing investment more in machines and reducing routine-task labor more than an average low-*RShare* firm. The findings on the degree of substitution suggest that the two opposite responses in investment and employment jointly constitute greater labor-technology substitution in bad times for high-*RShare* firms than for low-*RShare* firms. Taken together, these results support the model's core mechanism whereby firms with a higher *RShare* have more switching options (to replace their routine-task labor with machines in the face of unfavorable aggregate shocks).

C.4. Firm Performance and Aggregate Shocks

To further strengthen the link between the switching options and firm valuation, I explore how the value of high-*RShare* firms (i.e., firms with more switching options) responds to unfavorable shocks compared to the value of low-*RShare* firms. My model predicts that in the face of unfavorable shocks, firms exercise switching options, which reduce operating costs after labor-technology substitution is complete and prevent a decline in firm value. While there is little guidance on how long labor-technology substitution takes to complete, Kydland and Prescott (1982) find that a reasonable range for the average time-to-build is three to five quarters. Hence, I use an event study setting to examine how firms' operating cost and stock returns perform two years before and two years after recessions. Specifically, I define years 2001 and 2008 as event year 0 for the 2001 and 2008 to 2009 recessions, respectively. In event year -1, I sort firms into five quintiles based on their *RShare* within Fama-French 17 industries, $D(R_{f,-1})_d$, and I track these firms in event years $[-2,\ 1]$. I then set the dummy variable *Post* to one if the event year is 0 or 1 and to zero if the event year is -2 or -1. I use the following specification:

$$P_{f,t} = a_0 + \sum_{d=2}^{5} a_d D(R_{f,-1})_d + b_1 Post + \sum_{d=2}^{5} b_d D(R_{f,-1})_d \times Post + cX_{f,t} + F_{f\times Event} + \epsilon_{f,t}, \tag{25}$$

where $P_{f,t}$ is the measure of firm performance in event year t ($t = -2, -1, 0, 1$) and $F_{f\times Event}$ represents fixed effects of an interaction between the firm and the

Table X

Response of Firm Performance to Recessions and Expansions

This table shows the outcome of labor-technology substitution by reporting the performance of firms with different shares of routine-task labor (*RShare*) in the two years before and the two years during and after recessions (or expansions). Columns (1) to (3) report results for recessionary episodes, while columns (4) to (6) report results for expansionary episodes. A recessionary episode is defined as the four years around the 2001 and 2008 to 2009 recessions, while an expansionary episode is the four years around any year t with $[t-2, t+1]$ that do not include recession years during the period 1991 to 2014. $D(R)_d$ is a dummy quintile variable equal to 1 if the firm's *RShare* belongs in quintile d in the year before recessions or expansions. The breakpoints for the quintile sorting vary by industry. I use the 17-industry classification of Fama and French (1997). *Operating Cost* is firms' operating costs multiplied by 100. *Stock Returns* is firms' annual excess stock returns in percentage. *Machines* is firms' investment rate in machinery and equipment capital in percentage. See Appendix B for variable definitions. All regressions include firm-episode fixed effects. Columns (3) and (6) also include firm controls as in Table VIII for comparison. All standard errors are clustered at the firm-episode level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Post = Post Recessions			Post = Post Expansions		
Dep. Var.	Op. Cost (1)	Stock Ret. (2)	Machines (3)	Op. Cost (4)	Stock Ret. (5)	Machines (6)
Post	9.69***	−14.27***	−6.46***	−1.25**	−3.90***	−0.14
	(1.59)	(3.62)	(2.29)	(0.62)	(1.48)	(1.14)
$D(R)_2 \times Post$	−3.62*	−13.80**	2.69	−0.20	0.27	2.59*
	(2.08)	(6.99)	(3.29)	(0.76)	(1.88)	(1.40)
$D(R)_3 \times Post$	−4.32**	5.53	3.45	0.67	−0.72	0.25
	(1.92)	(4.75)	(2.83)	(0.75)	(1.83)	(1.41)
$D(R)_4 \times Post$	−4.84**	8.20*	6.63**	0.78	−1.10	0.51
	(1.88)	(4.68)	(2.79)	(0.75)	(1.78)	(1.35)
$D(R)_5 \times Post$	−5.09***	11.24**	6.23**	0.33	−2.57	1.86
	(1.97)	(4.87)	(2.55)	(0.76)	(1.81)	(1.32)
Observations	33,297	12,213	15,836	174,211	63,245	82,052
R^2	0.87	0.23	0.42	0.89	0.31	0.42

event episode. An event episode consists of the four years around the 2001 or the 2008 to 2009 recessions. I cluster standard errors at the firm-event level.

There are several advantages of using this setting. First, the two-year window helps detect delayed effects of labor-technology substitution on operating costs for some firms. Second, using recessions and expansions separates the negative shocks from the positive shocks, which helps identify the *hedging effects* of switching options on asset prices. Third, recessions represent strong negative aggregate shocks to business conditions, which helps reveal the outcome of labor-technology substitution by eliminating certain noise from the firm-level analyses.

Column (1) of Table X shows the differential changes in firm operating costs before and after recessions for high-*RShare* and low-*RShare* firms. The point estimates of $b_2, \ldots, b_5$ are all negative, and they increase in both statistical significance and economic magnitude from b_2 to b_5. This evidence suggests that firms with higher *RShare* performed relatively better in managing operating cost over the recessions. Column (2) shows the differential responses of stock returns. Low-*RShare* firms experience 14% lower annual stock returns over the recessions, while high-*RShare* experience only 3% lower returns over the recessions. The difference of 11% per year is remarkable, especially given that we are comparing firms within-industry.

C.5. Source of Risk: Negative versus Positive Shocks

As I discuss in Section I.D, for simplicity, my model abstracts from incorporating growth options. One potential concern with this simplification is that firms with different *RShare* may have differential exposure to positive economic shocks. To investigate this possibility, I examine changes in firm performance in the face of positive aggregate shocks.

I adopt the same setting as in equation (25), and I define "expansion" years as all nonrecession years in the period 1991 to 2014. To ensure that these tests are not contaminated by recession years, I further require that the four years around the expansion years not include the recession years, that is, 1991, 2001, 2008, and 2009. This filter leads to 11 expansionary episodes for the years 1994 to 1999, 2004 to 2006, and 2012 to 2013 during which the U.S. economy experienced positive growth (a 3.4% average growth rate in real GDP).

Columns (4) and (5) of Table X show the responses to the expansions for high- and low-*RShare* firms in terms of operating costs and stock return performance. Unlike responses to recessions, we find that the response of high-*RShare* firms to positive economic shocks is not significantly different from the response of low-*RShare* firms. This evidence mitigates the concern that the cross-sectional risk premia derive from risks associated with positive economic shocks, and helps justify the model's absence of growth options.

Finally, as a reality check to see whether the underlying investment mechanism also follows the sample pattern, I report firms' investment in machines as a response to recessions in column (3) and to expansions in column (6). Consistent with Figure 2, we observe a significant drop in investment in machines for low-*RShare* firms over recessions. High-*RShare* firms, in stark contrast, do not experience such a drop when controlling for common predictors of firm investment. In the placebo test, we do not observe significant differences in response to expansions between high-*RShare* and low-*RShare* firms.

C.6. Addressing Alternative Hypotheses

Heterogeneous Growth Opportunities: One alternative hypothesis for my findings on investment and employment is that firms with higher *RShare* may face fewer procyclical growth opportunities. This hypothesis implies that in bad times, high-*RShare* firms will cut investment less than low-*RShare* firms, regardless of the type of investment, and will also lay off fewer workers than low-*RShare* firms, regardless of the skill of workers. In contrast, my mechanism predicts that in bad times, high-*RShare* firms will cut investment in machines less than low-*RShare* firms, and high-*RShare* firms will lay off routine-task labor more than low-*RShare* firms.

I now provide evidence to differentiate my mechanism from this alternative hypothesis. On the investment side, I conduct a quasi-placebo test in which I run the regression in equation (22) but I examine investment in capital other than machines.[18] Column (3) of Table VIII shows that investment in other capital is not as resistant to aggregate shocks as investment in machines, on average. Moreover, in column (4), we do not observe significant differences for firms with different *RShare* in the cyclicality of their investment in other capital. The different response of investment in machines and investment in other capital is consistent with my mechanism, but it cannot be easily explained by the alternative hypothesis.

On the labor side, I examine the three-year change in establishments' share of routine-task employment, where this share is defined as the ratio of an establishment's routine-task employment to its total employment. I run the regression in equation (23) weighted by the average of the establishment's employment during the three-year gap. Columns (3) and (4) of Panel A in Table IX show that high-*RShare* firms respond to negative aggregate shocks by reducing their share of routine-task employment more than low-*RShare* firms. The differential response of this share suggests that high-*RShare* firms lay off *disproportionately* more routine-task workers than low-*RShare* firms in the face of unfavorable GDP shocks. I therefore conclude that high-*RShare* firms respond to unfavorable aggregate shocks by restructuring their labor composition, rather than simply scaling down their employment size. The alternative hypothesis, again, has difficulty explaining these differential changes in labor composition.

To provide additional evidence on the relation between investment in machines and layoffs of routine-task labor, in columns (3) and (4) of Panel B in Table IX, I conduct a quasi-placebo test by examining the sensitivity of routine-task employment to investment in other capital instead of investment in machines. I do not find the response of this sensitivity to aggregate shocks to be different between high-*RShare* and low-*RShare* firms.

In summary, while growth opportunities explain much of the aggregate investment and employment over the business cycle, growth opportunities alone appear to have difficulty explaining these new findings in the cross-section of firms. In contrast, these new findings are consistent with my mechanism of firms switching technologies during economic downturns. Without knowing the purpose of firm investment, one cannot fully separate the effect of technology-switching options from growth options. Examining how technology-switching options and growth options jointly shape a firm's total investment opportunities over the business cycle represents an interesting extension for future research.

[18] Other capital is measured as the difference between property, plant, and equipment at cost (Compustat item PPEGT) and machinery and equipment at cost (FATE). Note that other capital may also include certain necessary investments for labor-technology substitution. Due to an inability to exactly identify the type of investment associated with labor-technology substitution in the data, this quasi-placebo test should be regarded as suggestive.

Heterogeneous Fixed Adjustment Costs: One may also be tempted to explain my findings using heterogeneous fixed adjustment costs of routine-task labor versus other production factors. These alternative hypotheses argue that firms differ in their flexibility to respond to recessions rather than differ in their ability to engage in technology-switching during recessions. One way to distinguish these two mechanisms is to examine the longer term effects of recessions on firms. Specifically, while my mechanism predicts that firms' investment and employment change permanently after they switch their production technology, the alternative hypotheses based on the flexibility to adjust predict that firms' production structure "goes back to normal" after recessions.

I summarize the evidence that supports my mechanism. First, in Figure 1, I show that the lost routine-task jobs in the economy do not tend to bounce back after recessions, suggesting that the reduction in routine-task jobs in the economy is permanent. Second, in Table IX I demonstrate the differential responses of firms' routine-task employment to aggregate shocks in three-year horizons, suggesting that the extra reduction of routine-task labor in high-*RShare* firms is not a transitory labor policy for these firms. Third, in Figure 2 I show that the differential responses in machinery investment between high-*RShare* and low-*RShare* firms persist four years after the beginning of the recessions, indicating that labor-technology substitution is also persistent from firms' investment side. In summary, the evidence is consistent with my predicted mechanism whereby firms switch technology in the face of unfavorable aggregate shocks.

Cyclicality of Wages and Machine Prices: I next tie up the loose end around the fact that, for simplicity, my model abstracts from taking into account the dynamics of wages and machine prices. Specifically, one may be concerned that the main mechanism of this paper is driven by the wages of routine-task labor being stickier than the wages of nonroutine-task labor, or by firms expecting a drop in machine prices during bad times.

If the wages of routine-task labor are stickier than the wages of nonroutine-task labor, firms may respond to unfavorable shocks by laying off routine-task workers but reducing the wages of nonroutine-task workers. Overall, this is unlikely. In Panel A of Figure 3, I plot the average real hourly wages of routine-task labor and nonroutine-task labor from 1988 to 2015 using the sample from CPS-MORG. As can be seen, these two series are intimately correlated (correlation = 0.86), with the wages of routine-task labor slightly more cyclical.[19] This strong comovement between the wage series is further confirmed in regressions in Panel A of Table IX, where wages for firms' workers are measured more accurately. In this table, I report results on changes in the share of routine-task employment (column (4)) that do not account for worker wages, and changes in the share of routine-task wage expenses (column (6)) that account for the wages of routine workers and nonroutine workers in each firm.[20] I find that accounting for wages does not have a material effect on my results: high-*RShare* firms

[19] The correlation between the detrended real wages of routine-task labor and the detrended real GDP is 0.28; the correlation is 0.06 for the detrended real wages of nonroutine-task labor.

[20] Establishments' share of routine-task wage expenses is defined following equation (19).

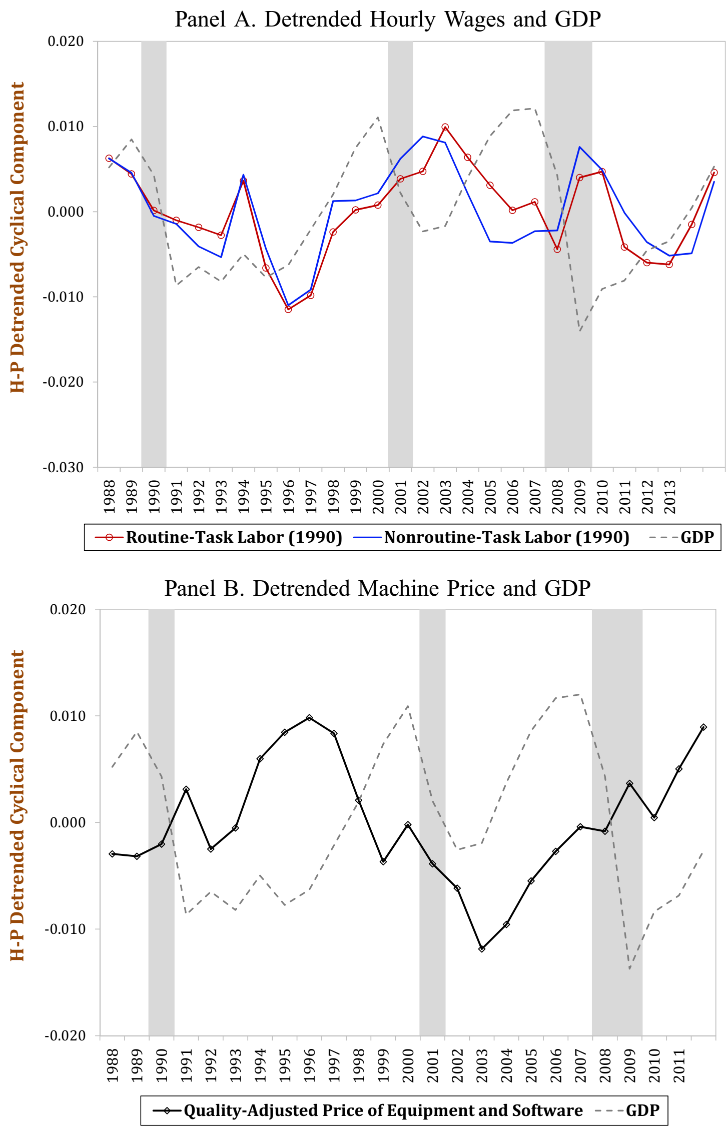

Figure 3. Wages and machine price index over the business cycle. Panel A presents the cyclicality of real hourly wages of routine-task labor and nonroutine-task labor classified based on the 1990 employment distribution (see Figure 1 for definitions). The two series of hourly wages are aggregated from individuals in the sample of the Current Population Survey Outgoing Rotation Group, and are weighted by the sample personal earnings weights. 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. (Color figure can be viewed at wileyonlinelibrary.com)

cut employment and total wage expenses on routine-task labor disproportionately more than low-*RShare* firms in the face of unfavorable shocks. Hence, my employment results are robust to incorporating wage dynamics.

The hypothesis based on the countercyclical price of machines does not contradict my model's main channel, as long as such a price pattern is well anticipated by firms. Nevertheless, in Panel B I plot the quality-adjusted price of equipment and software from 1988 to 2012 as a proxy for the price of technology (see Cummins and Violante (2002) and Kogan and Papanikolaou (2014)). Here, we observe that the price of technology drops during the 2001 recession but rises during the 1990 recession and during the 2008 to 2009 Great Recession. The correlation between the price of technology and GDP is -0.46, indicating that machines do not necessarily become cheaper in bad times. In summary, cyclical movements of wages and machine prices do not seem to offer an obvious mechanism for firms to undertake labor-technology substitution in bad times.

IV. 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 eventually replaced by the better tools. The adoption of new technologies to save labor costs 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 that 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 a labor-saving technology takes time and interrupts firm production, since the firm needs to adapt its production to the new technology (embodied in the machines). Because the cost induced by this 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 and thus have lower exposure to systematic risk than firms without routine-task labor.

I present novel empirical evidence that supports the main predictions of this model. Using detailed data at the establishment-occupation level, I calculate the proportion of a firm's total labor costs that can be potentially eliminated with automation—the share of routine-task labor—for publicly traded firms in the United States. I find that firms with a high share of routine-task labor have significantly lower market betas and lower expected returns than their industry peers. Inspecting the mechanism behind this phenomenon leads to supportive evidence that is strongly consistent with the model: firms with a high share of routine-task labor respond to unfavorable macroeconomic shocks by investing relatively more in machines than their industry peers and reducing more routine-task labor. As a result, firms with a high share of routine-task labor enjoy a larger cut in operating costs, and they experience a smaller reduction in market value than their industry peers in the face of the unfavorable shocks.

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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 the 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 the first passage time of drifted Brownian motion (see Shreve (2004), Section 8.3), we have $\hat{E}_t[e^{-r\tau}] = (\frac{A_t}{A^*})^{-v}$, where $v = \sqrt{(\frac{1}{2}+\frac{\sigma_x\sigma_\Lambda}{\sigma_a^2})^2 + \frac{2r}{\sigma_a^2}} - (\frac{1}{2}+\frac{\sigma_x\sigma_\Lambda}{\sigma_a^2})$. 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 in the following two steps:

Step 1: *Calculate the relation of portfolio beta to average cash flows.*

Let $F_U(t)$ denote the set of unautomated firms at time t, $F_A(t)$ denote the set of automated firms at time t, and $A_{u,t}$ and $A_{a,t}$ denote 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,

$$\begin{aligned}\beta_U(t) &= \frac{\int_{F_U(t)} V_u \beta_{u,t} du}{\int_{F_U(t)} V_u du} \\ &= -v + \frac{(1+v)\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{u,t}) - vV_u^f}{\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{u,t}) - V_u^f + \xi A^{*v}\int_{F_U(t)} A_{u,t}^{-v} du}\end{aligned} \tag{A1}$$

$$\leq -v + \frac{(1+v)\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{u,t}) - vV_u^f}{\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{u,t}) - V_u^f + \xi A^{*v}E(A_{u,t})^{-v}}.$$

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,

$$\beta_A(t) = \frac{\int_{F_A(t)} V_a\beta_{a,t}da}{\int_{F_A(t)} V_a da} \in \left[1 + \frac{V_a^f}{\frac{1}{r+\sigma_x\sigma_\Lambda}E(A_{a,t}) - \frac{f}{r}}, 1 + \frac{V_a^f}{\frac{e^{-(r+\sigma_x\sigma_\Lambda)T}}{r+\sigma_x\sigma_\Lambda}E(A_{a,t}) - \frac{f}{r}}\right]. \tag{A2}$$

As long as $E(A_{a,t})$ is bounded and $E(A_{u,t})$ increases without an upper bound over time, then after a 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 $E(A_{u,t}) = E(A_t \,|\, \min_{0\leq s\leq t} A_s \geq A^*)$, $E(A_{a,t}) = E(A_t \,|\, \min_{0\leq s\leq t} A_s < A^*)$, 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,

$$E(A_{u,t}) = A_0 E\left[e^{-\sigma W_t + \mu t} \,|\, \max_{0\leq s\leq t} W_s - \frac{\mu}{\sigma}s \leq \frac{1}{\sigma}\log\frac{A_0}{A^*}\right]. \tag{A3}$$

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

By Girsanov's Theorem, if we use $Z_\theta(t) = \exp(\theta W_t - \frac{1}{2}\theta^2 t)$ to define another probability measure $\tilde{\mathbb{P}}$, then

$$E[X] = \tilde{E}[XZ_\theta^{-1}(t)] \tag{A4}$$

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

$$\begin{aligned} E(A_{u,t}) &= A_0 \frac{E\left[e^{-\sigma \tilde{W}_t}1\{\max_{0\leq s\leq t}\tilde{W}_t \leq H\}\right]}{E\left[1\{\max_{0\leq s\leq t}\tilde{W}_t \leq H\}\right]} \\ &= A_0 \frac{\tilde{E}\left[e^{-\sigma\tilde{W}_t - \theta\tilde{W}_t - \frac{1}{2}\theta^2 t}1\{\max_{0\leq s\leq t}\tilde{W}_t \leq H\}\right]}{\tilde{E}\left[e^{-\theta\tilde{W}_t - \frac{1}{2}\theta^2 t}1\{\max_{0\leq s\leq t}\tilde{W}_t \leq H\}\right]} \\ &= A_0 \frac{g(-\sigma-\theta, H, t)}{g(-\theta, H, t)}, \end{aligned} \tag{A5}$$

where

$$g(\alpha, H, t) = \tilde{E}\left[e^{\alpha \tilde{W}_t} 1\{\max_{0\le s\le t} \tilde{W}_s \le H\}\right]. \tag{A6}$$

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):

$$\begin{aligned} g(\alpha, H, t) &= e^{\frac{1}{2}\alpha^2 t} \tilde{P}(\tilde{M}_t \le H) \\ &= e^{\frac{1}{2}\alpha^2 t}\left[\Phi\left(-\alpha\sqrt{t} + \frac{H}{\sqrt{t}}\right) - e^{2\alpha H}\left(1 - \Phi\left(\alpha\sqrt{t} + \frac{H}{\sqrt{t}}\right)\right)\right]. \end{aligned} \tag{A7}$$

Plugging (A7) into (A5) and noting that $\theta = \frac{\mu}{\sigma} = -\frac{1}{2}\sigma_a$, we have

$$\begin{aligned} E(A_{u,t}) &= A_0 \frac{g\left(-\frac{1}{2}\sigma_a, H, t\right)}{g\left(\frac{1}{2}\sigma_a, H, t\right)} \\ &= A_0 \frac{\Phi\left(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}\right) - e^{-\sigma_a H}\left(1 - \Phi\left(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}\right)\right)}{\Phi\left(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}\right) - e^{\sigma_a H}\left(1 - \Phi\left(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}\right)\right)}, \end{aligned} \tag{A8}$$

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 (A8) approaches $A_0(1 - e^{-\sigma_a H}) = A_0 - A^* > 0$, and the denominator approaches zero. Hence,

$$E(A_{u,t}) \to +\infty. \tag{A9}$$

Similarly, for automated firms, using Girsanov's Theorem, we have

$$E(A_{a,t}) = A_0 \frac{h(-\sigma - \theta, H, t)}{h(-\theta, H, t)}, \tag{A10}$$

where

$$h(\alpha, H, t) = \tilde{E}\left[e^{\alpha \tilde{W}_t} 1\{\max_{0\le s\le t} \tilde{W}_s > H\}\right]. \tag{A11}$$

Note that

$$g(\alpha, H, t) + h(\alpha, H, t) = \tilde{E}\left[e^{\alpha \tilde{W}_t}\right] = e^{\frac{1}{2}\alpha^2 t}. \tag{A12}$$

Hence, using equation (A7), we have

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

(A13)

Plugging (A13) into (A10), we have

$$\begin{aligned} E(A_{a,t}) &= A_0 \frac{h(-\frac{1}{2}\sigma_a, H, t)}{h(\frac{1}{2}\sigma_a, H, t)} \\ &= A_0 \frac{1 - \Phi\left(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}\right) + e^{-\sigma_a H}\left(1 - \Phi\left(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}\right)\right)}{1 - \Phi\left(-\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}\right) + e^{\sigma_a H}\left(1 - \Phi\left(\frac{1}{2}\sigma_a\sqrt{t} + \frac{H}{\sqrt{t}}\right)\right)}. \end{aligned} \tag{A14}$$

Given 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

$$E(A_{a,t}) \to A_0 e^{-\sigma_a H} = A^*. \tag{A15}$$

Plugging (A9) into (A1) and plugging (A15) into (A2), we have that as $t \to \infty$,

$$\beta_U(t) \to 1 \tag{A16}$$

and

$$\beta_A(t) \geq 1 + \frac{V_a^f}{\frac{1}{r+\sigma_x\sigma_\Lambda}A^* - \frac{f}{r}} > 1. \tag{A17}$$

Appendix B: Data and Sample Construction

I use primarily four data sets in this paper. First, I use OES microdata to construct firms' share of routine-task labor (*RShare*) and the three-year growth rates of establishments' routine-task employment. The OES program changed occupation classifications from 1998 to 1999. Thus, tracking three-year employment in a consistent occupation category is not feasible for the years 1999 to 2001. In addition, unique establishment identifiers are scarce before 1993. The sample period for calculating the three-year growth rate of establishments' routine-task employment is therefore restricted to the years 1996 to 1998 and 2002 to 2014.

Second, I use the CiTDB to obtain the growth rate of establishments' number of computers. This database, compiled from annual telephone surveys of establishments by the marketing and information company Harte-Hanks, includes roughly 500,000 establishments before 2010 and 3.2 million establishments afterward.[21] The data provide detailed information on establishments' stock of technology equipment, including desktops, laptops, printers, and servers.

[21] Harte-Hanks collects IT data primarily for the purpose of selling it to large producers and suppliers of IT, such as IBM and Cisco. The company is known for exerting strong market discipline on the quality (see Bloom, Sadun, and Van Reenen (2012)).

Following the literature (Bloom, Sadun, and Van Reenen (2012) and Tuzel and Zhang (2018)), I calculate the number of installed computers in an establishment as the total number of desktops and laptops, and I use the annual growth rate of the number of computers as a measure of an establishment's investment in computers. I further merge establishments to Compustat firms by legal names.

Third, I use Standard and Poor's Compustat annual industrial files to obtain firm-level accounting information, such as firms' investment in machines. I merge firms' *RShare* to Compustat firms to form a panel with an average of 4,297 firms per year from 1990 to 2014 to analyze firm investment in machines. Using the Compustat database as a bridge, I merge firms' *RShare* to CiTDB establishments to form a panel to analyze firm investment in computers. This sample has an average of 2,790 firms per year from 1990 to 2014.

Finally, monthly common stock data are from the Center for Research in Security Prices (CRSP share code SHRCD =10 or 11). The sample includes stocks listed on NYSE, NASDAQ, and Amex. I merge accounting information from Compustat to stock returns lagged by six months. I merge firms' *RShare* to their stock returns lagged by 18 months.[22]

When constructing the sample of stock returns, I exclude firms with market capitalization in the bottom 5% each year to avoid anomalies driven by micro-cap firms (Fama and French (2008)). To avoid survival bias in the data (Fama and French (1993)), I require firms in my sample to have appeared in Compustat for at least two years. Following the literature, I exclude firms with primary standard industrial classifications between 4900 and 4999 (regulated) and between 6000 and 6999 (financial).

I restrict my main analyses to be within the Fama-French 17-industry categories (Fama and French (1997)) for reasons discussed in Section I.D.[23] In light of the within-industry comparisons, I exclude firms that operate in many industries, such as conglomerates. Specifically, using Compustat Historical Segment data, I exclude firms with over 10% of yearly revenue coming from outside of their primary industry (i.e., the Fama-French 17-industry category that a firm's primary SIC belongs to). The final sample includes 525,244 monthly stock returns from July 1992 to June 2016.

I construct the following firm-level variables:[24]

[22] It takes BLS staff roughly one year to make the OES data available. Hence, investors and firms learn the distribution of occupations' RTI (and whether an occupation is routine) after one year. Donangelo (2014) adopts the same treatment when matching OES data to stock returns.

[23] Choosing the level of detail in the industry classification requires careful consideration. Specifically, the highly detailed industry classification may be inappropriate since it captures heterogeneity in industries' use of technology in performing similar tasks, for example, skilled nursing care facilities (SIC code 8051) may arguably use a better technology than intermediate care facilities (SIC code 8052). For this reason, I use the Fama-French 17-industry classification in the baseline analysis. In the Internet Appendix, I examine alternative industry classifications that are finer or coarser than the industry classification used in the baseline analysis.

[24] 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.

- *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 of productive structural capital.
- *Cash Flow* is cash flows defined as earnings before extraordinary items (IB) plus depreciation (DP) and normalized by capital stock (PPENT) at the beginning of the year.
- *Stock Ret* is firms' annual stock returns.
- *Op.Cost* is firms' operating costs, defined as the cost of goods sold (COGS) plus selling, general, and administrative expenses (SGA) and normalized by total assets (AT).
- *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.
- *B/M* is firms' book-to-market ratio, defined following Fama and French (1992).
- *Size* is the natural logarithm of firms' market capitalization.
- *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). The market value of the firm is the market value of common equity plus the book value of preferred stock (PSTK) plus total debt. The market value of common equity is defined as in Fama and French (1992).
- I^M is firms' investment rate in machines, calculated as the real growth rate of machinery and equipment at cost (FATE).
- I^O is firms' investment rate in other capital, calculated as the real growth rate of firms' physical capital other than machinery and equipment (PPEGT-FATE).
- *Shock* is the growth rate of real GDP.
- *Tobin's Q* is firms' Tobin's *Q*, defined as the ratio of firms' market value (the sum of total liabilities (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) and normalized by total assets (AT).
- *Assets* is firms' total assets (AT).

REFERENCES

Acemoglu, Daron, and David H. Autor, 2011, Skills, tasks and technologies: Implications for employment and earnings, in David Card and Orley Ashenfelter, eds.: *Handbook of Labor Economics*, *Vol. 4* (Elsevier, Amsterdam, the Netherlands).

Ai, Hengjie, and Dana Kiku, 2013, Growth to value: Option exercise and the cross-section of equity returns, *Journal of Financial Economics* 107, 325–349.

Atkin, David, Azam Chaudhry, Shamyla Chaudry, Amit K. Khandelwal, and Eric Verhoogen, 2017, Organizational barriers to technology adoption: Evidence from soccer-ball producers in Pakistan, *Quarterly Journal of Economics* 132, 1101–1164.

Autor, David H., and David Dorn, 2013, The growth of low-skill service jobs and the polarization of the U.S. labor market, *American Economic Review* 103, 1553–1597.

Autor, David H., Frank Levy, and Richard J. Murnane, 2003, The skill content of recent technological change: An empirical exploration, *Quarterly Journal of Economics* 118, 1279–1333.

Belo, Frederico, Jun Li, Xiaoji Lin, and Xiaofei Zhao, 2017, Labor-force heterogeneity and asset prices: The importance of skilled labor, *Review of Financial Studies* 30, 3669–3709.

Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.

Blinder, Alan S., and Alan B. Krueger, 2013, Alternative measures of offshorability: A survey approach, *Journal of Labor Economics* 31, S97–S128.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen, 2012, Americans do it better: U.S. multinationals and the productivity miracle, *American Economic Review* 102, 167–201.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt, 2002, Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence, *Quarterly Journal of Economics* 117, 339–376.

Brynjolfsson, Erik, and Lorin M. Hitt, 2003, Computing productivity: Firm-level evidence, *Review of Economics and Statistics* 85, 793–808.

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94, 1249–1275.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577–2603.

Chen, Huafeng Jason, Marcin Kacperczyk, and Hernan Ortiz-Molina, 2011, Labor unions, operating flexibility, and the cost of equity, *Journal of Financial and Quantitative Analysis* 46, 25–58.

Cooper, Russell W., and John C. Haltiwanger, 2006, On the nature of capital adjustment costs, *Review of Economic Studies* 73, 611–633.

Cummins, Jason G., and Giovanni L. Violante, 2002, Investment-specific technical change in the United States (1947-2000): Measurement and macroeconomic consequences, *Review of Economic Dynamics* 5, 243–284.

Davis, Steven J., John Haltiwanger, Kyle Handley, Ron Jarmin, Josh Lerner, and Javier Miranda, 2014, Private equity, jobs, and productivity, *American Economic Review* 104, 3956–3990.

Dixit, Avinash K., and Robert S. Pindyck, 1994, *Investment under Uncertainty* (Princeton University Press, Princeton, NJ).

Donangelo, Andres, 2014, Labor mobility: Implications for asset pricing, *Journal of Finance* 69, 1321–1346.

Eisfeldt, Andrea L., and Dimitris Papanikolaou, 2013, Organization capital and the cross-section of expected returns, *Journal of Finance* 68, 1365–1406.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653–1678.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Garleanu, Nicolae, Stavros Panageas, and Jianfeng Yu, 2012, Technological growth and asset pricing, *Journal of Finance* 67, 1265–1292.

Gomes, Joao F., Leonid Kogan, and Lu Zhang, 2003, Equilibrium cross section of returns, *Journal of Political Economy* 111, 693–732.

Goos, Maarten, Alan Manning, and Anna Salomons, 2014, Explaining job polarization: Routine-biased technological change and offshoring, *American Economic Review* 104, 2509–2526.

Gordon, Robert J., 1990, *The Measurement of Durable Goods Prices* (University of Chicago Press, Chicago, IL).

Gourio, Francois, 2007, Labor leverage, firms' heterogeneous sensitivities to the business cycle, and the cross-section of expected returns, Working paper, Federal Reserve Bank.

Greenwood, Jeremy, 1999, The third industrial revolution: Technology, productivity, and income inequality, *Economic Review* 35, 2–12.

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell, 1997, Long-run implications of investment-specific technological change, *American Economic Review* 87, 342–362.

Hackbarth, Dirk, and Timothy Johnson, 2015, Real options and risk dynamics, *Review of Economic Studies* 82, 1449–1482.

Hershbein, Brad J., and Lisa B. Kahn, 2018, Do recessions accelerate routine-biased technological change? Evidence from vacancy postings, *American Economic Review* 108, 1737–1772.

Hirsch, Barry T., and David A. MacPherson, 2003, Union membership and coverage database from the Current Population Survey: Note, *Industrial and Labor Relations Review* 56, 349–354.

Israelsen, Ryan D., 2010, Investment-based valuation and managerial expectations, Working paper, University of Indiana.

Jaimovich, Nir, and Henry E. Siu, 2014, The trend is the cycle: Job polarization and jobless recoveries, NBER Working Paper.

Kogan, Leonid, and Dimitris Papanikolaou, 2014, Growth opportunities, technology shocks, and asset prices, *Journal of Finance* 69, 675–718.

Kuehn, Lars-Alexander, Mikhail Simutin, and Jessie Jiaxu Wang, 2017, A labor capital asset pricing model, *Journal of Finance* 72, 2131–2178.

Kydland, Finn E., and Edward C. Prescott, 1982, Time to build and aggregate fluctuations, *Econometrica* 50, 1345–1370.

Lewellen, Jonathan, and Stefan Nagel, 2006, The conditional CAPM does not explain asset-pricing anomalies, *Journal of Financial Economics* 82, 289–314.

Liu, Laura Xiaolei, Toni M. Whited, and Lu Zhang, 2009, Investment-based expected stock returns, *Journal of Political Economy* 117, 1105–1139.

Manuelli, Rodolfo E., and Ananth Seshadri, 2014, Frictionless technology diffusion: The case of tractors, *American Economic Review* 104, 1368–1391.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Novy-Marx, Robert, 2011, Operating leverage, *Review of Finance* 15, 103–134.

Ochoa, Marcelo, 2013, Volatility, labor heterogeneity and asset prices, Working paper, Federal Reserve Board.

Papanikolaou, Dimitris, 2011, Investment shocks and asset prices, *Journal of Political Economy* 119, 639–685.

Shreve, Steven E., 2004, *Stochastic Calculus for Finance II: Continuous-Time Models*, Vol. 11 (Springer Science & Business Media, Berlin).

Tuzel, Selale, 2010, Corporate real estate holdings and the cross-section of stock returns, *Review of Financial Studies* 23, 2268–2302.

Tuzel, Selale, and Miao Ben Zhang, 2017, Local risk, local factors, and asset prices, *Journal of Finance* 72, 325–370.

Tuzel, Selale, and Miao Ben Zhang, 2018, Economic stimulus at the expense of routine-task jobs, Working paper, University of Southern California.

Weber, Michael, 2015, Nominal rigidities and asset pricing, Working paper, University of Chicago.

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.