Internet Appendix for "Labor-Technology Substitution: Implications for Asset Pricing"

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Section I of this appendix presents results of supplementary robustness checks. Section II provides additional technical details on data, measures, figures, and tables. Section III develops and calibrates an extended model of the simple technology-switching model presented in the main text.

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I. Supplementary Results

Table IAI
Most and Least Routine Occupations

This table reports the 10 occupations with the highest and the 10 occupations with the lowest routine-task intensity (RTI) scores, as of 2014.

SOC	Occupation Title	RTI Score
	Panel A: Top 10 Occupations with the Highest Routine-Task Intensity Score	
43-9051	Mail Clerks and Mail Machine Operators, Except Postal Service	1.66
43-4071	File Clerks	1.65
51-9031	Cutters and Trimmers, Hand	1.64
51-3093	Food Cooking Machine Operators and Tenders	1.62
51-9022	Grinding and Polishing Workers, Hand	1.61
51-6062	Textile Cutting Machine Setters, Operators, and Tenders	1.57
43-6012	Legal Secretaries	1.54
43-4021	Correspondence Clerks	1.47
53-7011	Conveyor Operators and Tenders	1.47
23-2091	Court Reporters	1.42
	Panel B: Bottom 10 Occupations with the Lowest Routine-Task Intensity Score	
39-9031	Fitness Trainers and Aerobics Instructors	-2.98
33-1021	First-Line Supervisors of Fire Fighting and Prevention Workers	-2.95
17-2021	Agricultural Engineers	-2.73
19-3092	Geographers	-2.73
11-9021	Construction Managers	-2.61
13-1141	Compensation, Benefits, and Job Analysis Specialists	-2.53
21-1094	Community Health Workers	-2.53
53-5031	Ship Engineers	-2.41
25-2012	Kindergarten Teachers, Except Special Education	-2.38
53-4011	Locomotive Engineers	-2.28

Table IAII—Robustness of Asset Pricing
Alternative Industry Classifications in Panel Regressions

This table reports results of robustness tests on the panel regressions on conditional beta (in Panel A) and annual stock returns (in Panel B) using alternative industry classifications. Conditional beta is constructed using 12 monthly stock returns following Lewellen and Nagel (2006). *Baseline* uses the Fama-French 17-industry classification. $FF49$ uses the Fama-French 49-industry classification. *SIC1* and *SIC2* use the one-digit SIC industry sector classification and two-digit SIC industry classification, respectively. *HP50* and *HP100* use the 10-K text-based fixed industry classifications as in Hoberg and Phillips (2010); Hoberg and Phillips (2016) with 50 and 100 industry categories, respectively. *No Ind.* means running the regression without industry fixed effects. All standard errors are double clustered at the firm and year level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1992 to June 2016.

Panel A: Conditional Betas							
	Baseline	FF49	SIC1	SIC2	HP50	HP100	No Ind.
$RShare_{t-1}$	−0.54***	−0.36***	−0.52***	−0.41***	−0.37***	−0.29***	−0.48***
	(0.14)	(0.14)	(0.11)	(0.12)	(0.10)	(0.09)	(0.13)
Firm Control	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Yr
Observations	40,416	40,416	40,416	40,416	31,988	31,988	40,416
Adj. R^2	0.07	0.09	0.06	0.09	0.11	0.12	0.05
Panel B: Annual Stock Returns							
	Baseline	FF49	SIC1	SIC2	HP50	HP100	No Ind.
$RShare_{t-1}$	−9.00***	−9.04***	−11.62***	−9.23***	−10.46***	−7.70**	−11.85**
	(3.25)	(3.00)	(4.31)	(3.25)	(3.88)	(3.90)	(5.04)
Firm Control	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Ind×Yr	Yr
Observations	40,416	40,416	40,416	40,416	31,988	31,988	40,416
Adj. R^2	0.15	0.18	0.14	0.17	0.19	0.19	0.12

Table IAIII—Robustness of Asset Pricing Panel Regressions with Subsamples by Industry Sectors

This table presents results of panel regression on stock returns within each one-digit SIC industry sector. Firm controls include operating leverage, book-to-market ratio, operating cost, cash flows, size, and market leverage (see Appendix A in the main text for definitions). All standard errors are double clustered at the firm and year level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1992 to June 2016.

Panel A: Conditional Betas							
Sector	Mining	Construction	Manufacture	Transportation	Wholesale	Retail	Service
RShare_{t-1}	−6.64	−38.19*	−17.10***	−7.77	−16.40	−10.27**	0.07
	(12.37)	(22.10)	(6.41)	(15.25)	(11.19)	(5.12)	(8.56)
Firm Control	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,452	554	20,897	2,214	1,759	4,271	9,013
Adj. R^2	0.33	0.28	0.13	0.13	0.16	0.24	0.13

Panel B: Annual Stock Returns							
Sector	Mining	Construction	Manufacture	Transportation	Wholesale	Retail	Service
RShare_{t-1}	−0.28	−0.34	−0.64***	0.05	−0.53	−0.99***	−0.13
	(0.61)	(1.62)	(0.13)	(0.65)	(0.37)	(0.26)	(0.30)
Firm Control	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,452	554	20,897	2,214	1,759	4,271	9,013
Adj. R^2	0.19	0.13	0.05	0.07	0.02	0.05	0.06

Table IAIV—Robustness of Asset Pricing
Five Portfolios Sorted on *RShare* without Industry Control

This table reports time-series averages of stock returns for five portfolios sorted on the share of routine-task labor (*RShare*). At the end of each June, firms are sorted into five value-weighted portfolios based on their *RShare*. *Mean Excess Returns* are monthly returns minus the one-month Treasury bill rate. *Unconditional CAPM* and *Conditional CAPM* correspond to the unconditional CAPM time-series regressions and the conditional CAPM regressions following Lewellen and Nagel (2006), respectively. Newey and West (1987) standard errors, reported in parentheses, are estimated with four lags for the portfolio returns and unconditional CAPM and with one lag for the conditional CAPM. All returns, alphas, and their standard errors are annualized by multiplying by 12 and are reported in percentages. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1992 to June 2016.

	L	2	3	4	H	H−L
			Mean Excess Returns			
$E[R] - r_f$ (%)	9.56**	8.71**	8.29**	8.04**	6.58**	−2.98*
	(4.41)	(3.50)	(3.40)	(3.33)	(2.80)	(1.67)
			Unconditional CAPM			
MKT β	1.25***	0.98***	1.02***	0.93***	0.87***	−0.38***
	(0.07)	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)
α (%)	0.13	1.26	0.60	0.99	−0.00	−0.14
	(2.29)	(1.37)	(1.19)	(1.14)	(1.23)	(2.42)
R^2	0.75	0.85	0.87	0.87	0.82	0.18
			Conditional CAPM			
Avg. MKT β	1.15***	0.95***	0.98***	0.91***	0.87***	−0.28***
	(0.07)	(0.07)	(0.05)	(0.04)	(0.04)	(0.08)
Avg. α (%)	2.71	1.81	1.00	1.17	0.51	−2.23
	(2.07)	(1.62)	(1.20)	(1.02)	(0.89)	(2.45)
Avg. R^2	0.78	0.87	0.85	0.88	0.82	0.28

Table IAV—Robustness of Asset Pricing
Excess Returns and CAPM Betas in Subsamples by Firm Size

This table reports mean excess return and unconditional CAPM time-series regression results for large firms (firms with above-median size within industry-year) and small firms. At the end of each June, firms in each sample are sorted into value-weighted portfolios based on their *RShare* within Fama-French 17 industries. Newey and West (1987) standard errors, reported in parentheses, are estimated with four lags. All returns, CAPM alphas, and their standard errors are annualized by multiplying by 12 and are reported in percentages. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1992 to June 2016.

	L	2	3	4	H	H−L
			Panel A. Large Firms			
$E[R] - r_f$ (%)	10.02**	9.11**	9.21***	8.41***	6.22**	−3.81*
	(3.93)	(3.89)	(3.42)	(2.95)	(3.02)	(2.23)
MKT β	1.09***	1.08***	1.02***	0.87***	0.86***	−0.23***
	(0.05)	(0.03)	(0.03)	(0.02)	(0.04)	(0.06)
α (%)	1.78	0.95	1.52	1.82*	−0.28	−2.06
	(1.82)	(1.66)	(1.09)	(1.03)	(1.32)	(2.12)
			Panel B. Small Firms			
$E[R] - r_f$ (%)	13.79**	12.87**	12.79**	11.80**	10.61**	−3.18
	(5.77)	(5.33)	(4.98)	(5.04)	(4.80)	(1.81)
MKT β	1.30***	1.27***	1.19***	1.11***	1.14***	−0.15**
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
α (%)	3.96	3.28	3.75	3.37	1.95	−2.01
	(3.63)	(3.40)	(3.12)	(3.20)	(2.86)	(2.35)

Table IAVI—Robustness of Asset Pricing
Five Employment-Weighted Portfolios Sorted on *RShare*

This table reports the time-series averages of stock returns for five portfolios sorted on the share of routine-task labor (*RShare*). At the end of each June, firms in each Fama-French 17 industry are sorted into five employment-weighted portfolios based on their *RShare*. *Mean Excess Returns* are monthly returns minus the 1-month Treasury bill rate. *Unconditional CAPM* and *Conditional CAPM* correspond to the unconditional CAPM time-series regressions and conditional CAPM regressions following Lewellen and Nagel (2006), respectively. Newey and West (1987) standard errors, reported in parentheses, are estimated with four lags for the portfolio returns and unconditional CAPM and with one lag for the conditional CAPM. All returns, alphas, and their standard errors are annualized by multiplying by 12 and are reported in percentages. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1992 to June 2016.

	L	2	3	4	H	H−L
			Mean Excess Returns			
$E[R] - r_f$ (%)	12.05***	8.45*	8.54**	10.46***	8.37**	−3.68*
	(4.10)	(4.37)	(4.16)	(3.13)	(3.90)	(2.00)
			Unconditional CAPM			
MKT β	1.12***	1.13***	1.06***	0.86***	0.92***	−0.20***
	(0.06)	(0.07)	(0.07)	(0.04)	(0.08)	(0.06)
α (%)	3.59	−0.12	0.52	3.97**	1.41	−2.18
	(2.35)	(2.77)	(2.55)	(1.77)	(2.58)	(2.07)
R^2	0.73	0.71	0.70	0.72	0.57	0.07
			Conditional CAPM			
Avg. MKT β	1.21***	1.20***	1.13***	0.96***	0.96***	−0.25***
	(0.08)	(0.08)	(0.10)	(0.06)	(0.10)	(0.08)
Avg. α (%)	3.31	0.60	1.10	1.86	1.45	−1.87
	(2.99)	(3.94)	(3.04)	(2.03)	(2.32)	(2.59)
Avg. R^2	0.75	0.79	0.78	0.73	0.62	0.28

Table IAVII—Robustness of Asset Pricing
Full Matrix of 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 a firm characteristic. Within each bin, I further sort firms into five value-weighted portfolios based their *RShare*, resulting in fifteen portfolios in total. See Appendix A in the main text for definitions of firm characteristics. Newey and West (1987) standard errors, reported in parentheses, are estimated with four lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample covers stock returns from July 1992 to June 2016.

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
	Conditional on Operating Leverage							*Conditional on Book-to-Market Ratio*					
Low	1.09***	1.10***	1.10***	0.95***	0.90***	-0.19***	Low	1.13***	1.09***	1.08***	0.93***	0.80***	-0.33***
	(0.06)	(0.06)	(0.05)	(0.03)	(0.03)	(0.07)		(0.09)	(0.06)	(0.05)	(0.04)	(0.03)	(0.09)
Medium	1.22***	1.08***	0.92***	0.77***	0.77***	-0.46***	Medium	1.20***	1.10***	0.91***	0.79***	0.95***	-0.25***
	(0.10)	(0.05)	(0.05)	(0.04)	(0.07)	(0.13)		(0.06)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)
High	1.11***	0.96***	0.97***	1.02***	0.76***	-0.35***	High	1.13***	0.99***	0.90***	0.95***	0.94***	-0.20***
	(0.08)	(0.08)	(0.07)	(0.08)	(0.06)	(0.11)		(0.07)	(0.06)	(0.07)	(0.05)	(0.06)	(0.08)
	Conditional on Operating Cost							*Conditional on Size*					
Low	1.11***	1.18***	1.03***	1.03***	0.95***	-0.16*	Low	1.27***	1.18***	1.17***	1.14***	1.06***	-0.21**
	(0.08)	(0.06)	(0.05)	(0.07)	(0.03)	(0.09)		(0.07)	(0.08)	(0.09)	(0.08)	(0.07)	(0.08)
Medium	1.16***	1.02***	1.01***	0.88***	0.92***	-0.25***	Medium	1.32***	1.21***	1.18***	1.08***	1.12***	-0.20***
	(0.06)	(0.07)	(0.05)	(0.04)	(0.05)	(0.08)		(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
High	1.10***	0.98***	0.87***	0.77***	0.85***	-0.25**	High	1.10***	1.03***	1.00***	0.85***	0.86***	-0.24***
	(0.08)	(0.05)	(0.05)	(0.06)	(0.06)	(0.10)		(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)
	Conditional on Operating Cash Flow							*Conditional on Market Leverage*					
Low	1.31***	1.30***	1.14***	1.24***	1.02***	-0.29***	Low	1.14***	1.09***	1.06***	1.11***	0.97***	-0.17*
	(0.09)	(0.08)	(0.09)	(0.05)	(0.06)	(0.06)		(0.06)	(0.08)	(0.07)	(0.04)	(0.09)	(0.09)
Medium	1.07***	0.91***	0.89***	0.73***	0.85***	-0.21***	Medium	1.16***	0.97***	0.98***	0.78***	0.84***	-0.32***
	(0.07)	(0.04)	(0.03)	(0.04)	(0.06)	(0.07)		(0.06)	(0.05)	(0.04)	(0.03)	(0.04)	(0.08)
High	0.97***	1.08***	1.15***	0.97***	0.92***	-0.05	High	1.12***	0.94***	0.97***	0.87***	0.95***	-0.17*
	(0.06)	(0.06)	(0.07)	(0.04)	(0.07)	(0.11)		(0.07)	(0.06)	(0.04)	(0.08)	(0.07)	(0.10)

Table IAVIII—Robustness of Asset Pricing
Panel Regression on Share of Routine-Cognitive and Routine-Manual Labor

This table reports results on the predictability of firms' share of routine-task labor (*RShare*), share of routine-cognitive labor (*RCShare*), and share of routine-manual labor (*RMShare*) on their conditional betas and annual stock returns, while controlling for firm characteristics known to predict risk. Occupations are defined as routine-cognitive if they are classified as routine-task and they are also in the following broad occupation categories: "management, business, and financial operations occupations," "professional and related occupations," "sales and related occupations," and "office and administrative support occupations" (Jaimovich and Siu (2014)). I define the remainder of the routine-task occupations as routine-manual. Conditional betas are calculated following Lewellen and Nagel (2006) for each year t. Annual stock returns are in percentages. See Appendix A of the main text for definitions of firm characteristics. All regressions include industry-year fixed effects, where I use the 17-industry classification of Fama and French (1997). Standard errors are clustered at both the firm and the year level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
			Panel A: Conditional Betas		
$RShare_{t-1}$	-0.59^{***}				
	(0.14)				
$RCShare_{t-1}$		-0.48^{**}		-0.60^{***}	-0.44^{**}
		(0.21)		(0.22)	(0.21)
$RMShare_{t-1}$			-0.53^{***}	-0.59^{***}	-0.57^{***}
			(0.14)	(0.15)	(0.14)
Firm Control	N	N	N	N	Y
Observations	40,416	40,416	40,416	40,416	40,416
Adjusted R^2	0.07	0.07	0.07	0.07	0.07
			Panel B: Annual Stock Returns		
$RShare_{t-1}$	-6.49^{*}				
	(3.46)				
$RCShare_{t-1}$		-3.38		-4.82	-12.67^{*}
		(6.71)		(6.80)	(7.17)
$RMShare_{t-1}$			-6.70^{*}	-7.13^{**}	-7.64^{**}
			(3.51)	(3.58)	(3.37)
Firm Control	N	N	N	N	Y
Observations	40,416	40,416	40,416	40,416	40,416
Adjusted R^2	0.13	0.13	0.13	0.13	0.15

Table IAIX—Table IX with Full Coefficients
Response of Firm Technology Investment to Aggregate Shocks

This table reports regression results in Table IX in the main text with full coefficients. In Table IX, coefficients on *RShare* quintile dummies and firm-level controls are not reported for brevity. See Table IX and Appendix B in the main text for more details. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Compustat Firms				*CiTDB Establishments*	
Dep. Var.	Machines		Other Capital		Computers	
	(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)
$D(R)_2$		−0.37		−0.61		2.52**
		(0.97)		(1.88)		(1.01)
$D(R)_3$		−0.91		−1.00		2.09**
		(0.98)		(1.81)		(0.98)
$D(R)_4$		−1.17		0.65		2.06**
		(0.98)		(1.96)		(1.02)
$D(R)_5$		−0.30		0.43		2.94***
		(0.97)		(1.81)		(1.07)
Tobin's Q	13.51***	13.47***	19.39***	19.38***	0.84	0.79
	(0.75)	(0.75)	(1.45)	(1.44)	(0.59)	(0.59)
Mkt.Lev	−19.12***	−19.17***	−26.02***	−26.08***	−0.92	−1.03
	(1.91)	(1.91)	(3.10)	(3.10)	(1.42)	(1.41)
Cash Flow	0.01	0.01	0.12	0.12	0.03	0.03
	(0.05)	(0.05)	(0.10)	(0.10)	(0.03)	(0.03)
Cash Holding	31.16***	31.09***	47.54***	47.46***	−6.70***	−6.78***
	(2.99)	(2.99)	(5.57)	(5.57)	(1.95)	(1.95)
Assets	−6.15***	−6.07***	−7.11***	−7.12***	−2.46***	−2.48***
	(0.46)	(0.46)	(0.75)	(0.76)	(0.31)	(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

Table IAX—Table X with Full Coefficients
Response of Firm Routine-Task Employment to Aggregate Shocks

This table reports the regression results in Table X in the main text with full coefficients. In Table X, coefficients on *RShare* quintile dummies and interaction terms related to $D(R)_2$ and $D(R)_3$ are not reported for brevity. See Table X and Appendix B in the main text for more details. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Routine-Task Employment

Dep. Var.	Routine Employment		Share of Routine Employment		Share of Routine Wage Bill	
	(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)
$D(R)_2$		−58.70***		−6.98***		−5.03***
		(4.16)		(0.59)		(0.49)
$D(R)_3$		−81.37***		−11.78***		−9.43***
		(4.21)		(0.66)		(0.55)
$D(R)_4$		−103.03***		−17.80***		−14.46***
		(4.27)		(0.73)		(0.62)
$D(R)_5$		−131.77***		−29.26***		−25.41***
		(4.52)		(0.91)		(0.80)
# 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

Table IAX — *Continued*

Panel B: Sensitivity of Routine-Task Employment to Investment				
Dep. Var.	Routine Employment			
	I = Machines		I = Other Capital	
	(1)	(2)	(3)	(4)
I	0.01	0.07*	0.03***	−0.04
	(0.01)	(0.04)	(0.01)	(0.04)
$I \times D(R)_2$	0.02	−0.01	−0.01	0.07
	(0.03)	(0.07)	(0.01)	(0.04)
$I \times D(R)_3$	0.00	−0.11	−0.04***	0.01
	(0.02)	(0.08)	(0.01)	(0.05)
$I \times D(R)_4$	−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)
$I \times D(R)_2 \times Shock$		0.17		−1.06**
		(0.65)		(0.53)
$I \times D(R)_3 \times Shock$		0.75		−0.56
		(0.77)		(0.57)
$I \times D(R)_4 \times Shock$		0.88*		−0.16
		(0.49)		(0.77)
$I \times D(R)_5 \times Shock$		1.10**		−1.04*
		(0.50)		(0.53)
$D(R)_2 \times Shock$		0.96		1.42
		(0.99)		(1.02)
$D(R)_3 \times Shock$		1.04		1.50
		(0.94)		(0.96)
$D(R)_4 \times Shock$		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)
$D(R)_2$	−0.55***	−0.60***	−0.54***	−0.63***
	(0.05)	(0.08)	(0.05)	(0.08)
$D(R)_3$	−0.72***	−0.77***	−0.70***	−0.79***
	(0.05)	(0.08)	(0.05)	(0.08)
$D(R)_4$	−0.92***	−0.97***	−0.92***	−0.98***
	(0.05)	(0.08)	(0.05)	(0.08)
$D(R)_5$	−1.15***	−1.22***	−1.13***	−1.24***
	(0.06)	(0.08)	(0.06)	(0.08)
Observations	66,785	66,785	66,392	66,392
Adjusted R^2	0.14	0.14	0.14	0.14

Table IAXI—Robustness of the Mechanism
Firm Technology Investment with Ind-Year Fixed Effects

This table reports results of robustness tests of firms' investment response to aggregate shocks to including industry-year fixed effects. 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 CiTDB data. *Shock* is real GDP growth from $t-1$ to t. $D(R)_i$ is a dummy quintile variable equal to one if the firm's *RShare* belongs in quintile i at year $t-1$, where breakpoints vary by industry. I use the 17-industry classification of Fama and French (1997). All regressions include a vector of controls of industry-year fixed effects, firm fixed effects, and lagged values of log Tobin's Q, market leverage, cash flows, cash holdings, and log total assets. Coefficients on quintile dummies and firm controls are not reported. See Appendix A in the main text for definitions of these variables. Establishment-level regressions in columns (5) and (6) are weighted by an establishment's number of computers within the firm in $t-1$. All standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Compustat Firms		*CiTDB Establishments*
Dep. Var.	Machines (1)	Other Capital (2)	Computers (3)
$D(R)_2 \times Shock$	-0.61^{*}	-0.23	-0.47
	(0.33)	(0.64)	(0.31)
$D(R)_2 \times Shock$	-0.74^{**}	-0.24	-0.56^{*}
	(0.32)	(0.61)	(0.30)
$D(R)_2 \times Shock$	-0.81^{**}	-0.58	-0.63^{**}
	(0.32)	(0.61)	(0.30)
$D(R)_2 \times Shock$	-0.98^{***}	-0.62	-0.90^{***}
	(0.31)	(0.60)	(0.31)
Observations	41,601	40,403	1,405,940
Adjusted R^2	0.23	0.15	0.13

Table IAXII—Robustness of the Mechanism
Firm Routine-Task Employment with Industry-Year Fixed Effects

This table presents results of robustness tests of firms' employment response to aggregate shocks to including industry-year fixed effects. Change in *Routine Employment* is the establishment's three-year change in employment of routine-task labor normalized by the average of the establishment's routine-task employment in year $t-3$ 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* 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, which restricts the sample period for this test to 1996 to 1998 and 2002 to 2014 in columns (1) and (2) and 2002 to 2014 in column (3) since wage data are available in microdata after 1998 (see Appendix A in the main text for more details). *Shock* is real GDP growth from $t-3$ to t. $D(R)_i$ is a dummy quintile variable equal to one if the firm's *RShare* belongs in quintile i at year $t-3$, where breakpoints vary by industry. I use the 17-industry classification of Fama and French (1997). Coefficients of quintile dummies are not report. All regressions include industry-year fixed effects as well as firm fixed effects. I weight establishments within each firm-year for all regressions. The weights are the average of establishments' routine-task employment in $t-3$ and t when dependent variable is routine employment, and average 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, reported in parentheses, are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	Routine Employment (1)	Share of Routine Employment (2)	Share of Routine Wage (3)
$D(R)_2 \times Shock$	1.45***	0.12	0.06
	(0.54)	(0.08)	(0.07)
$D(R)_3 \times Shock$	1.83***	0.19**	0.19***
	(0.52)	(0.08)	(0.07)
$D(R)_4 \times Shock$	1.66***	0.19**	0.11
	(0.52)	(0.08)	(0.08)
$D(R)_5 \times Shock$	1.97***	0.35***	0.29***
	(0.51)	(0.10)	(0.09)
Observations	41,601	40,403	1,405,940
Adjusted R^2	0.13	0.13	0.13

II. Technical Details

Imputation of Wages for OES Establishments Before 1998. The raw microdata of the OES program provide 12 buckets for hourly wages for each occupation starting in 1998. In other words, the raw data provide the number of employees at establishment-occupation-wage bucket level. I thus estimate median hourly wages for each occupation in each establishment from 1998 onwards. The OES microdata do not have wage information before 1998. Thus, for years before 1998, I estimate hourly wages from the Census Current Population Survey Merged Outgoing Rotation Groups (CPS-MORG). Specifically, from the CPS-MORG, I calculate hourly wages for 504 occupations in 13 broad industries by averaging hourly wages of individuals aged from 18 to 65 within each group, weighted by the personal earnings weights. To crosswalk a Census occupation to an OES occupation, I link Census and OES occupational codes to a finer occupational classification—the Dictionary of Occupational Titles (DOT)—and build the crosswalk if the Census occupation covers more than 50% of the DOT occupations that the OES covers. When possible, I impute the hourly wage for each occupation-industry (three-digit SIC) in the OES microdata. Otherwise, I use either the estimated nationwide hourly wage for the OES occupation or the industry-level hourly wage for the major group of the OES occupation. The total wage paid to an occupation in an establishment is simply the product of employment and the hourly wage.

Matching OES Establishments and Compustat Firms. My matching of OES establishment and Compustat firms relies in part on employer identification number (EIN). The OES program began to record the parent firm's EIN for establishments after 1999. For the sample between 1990 and 1999, I back out the EIN information by linking OES establishments through the BLS's internal identifiers to the Quarterly Census of Employment and Wages (QCEW) microdata, which record the EIN for the universe of establishments from 1990 to 2014. For the OES sample in 1988 and 1989, I match the establishments to Compstat firms using legal names as no EINs are available.

The second part of the matching is conducted based on name matching. To do so, I first purge names of the OES establishments and of Compustat firms. The OES data report the legal name and the trade name of the establishments. Sometimes, neither of these names corresponds to the names of the establishment's parent firm. I thus employ another data set, ReferenceUSA, which provides the near-universe of all establishments in the U.S. and the link between establishments and their parent firms.[1] After making these efforts to learn the naming of establishments, I adjust my code for purging the names of establishments to improve the name matching.

Additional Details of Drawing Figure 1. Given that the OES data underwent a major change in occupation classification in 1999, they are not suitable for time-series analysis that requires tracking a given set of occupations over time. I thus use the CPS monthly data, which have a time-series consistent measure of occupation, *occ*1990, from the Integrated Public Use Microdata Series database. I classify occupations based on the distribution of RTI scores using 1990 Census data. Specifically, I classify each occupation in the 1990 Census as *routine-task labor (1990)* or *nonroutine-task labor (1990)* using the methodology described in Section 2.1 in the main text. I then track the employment of these two groups of occupations from January 1988 to December 2015.

Grouping of Occupations in Table I. The OES microdata use the OES Taxonomy classification for occupations before 1998, and adopt the Standard Occupational Classification (SOC) for occupations after 1998. In Table I, I aggregate occupations to their major group level in the OES Taxonomy classification system for the 1990 to 1998 sample. For the 1999 to 2014 sample, I aggregate the major SOC classification to seven aggregate groups following the suggestions of the SOC Revision Policy Committee. Specifically, *Management* represents managerial and administration occupations (SOC 11-13), *Professional* represents professional, paraprofessional, and technical occupations (SOC 15-31), *Sales* represents sales-related occupations (SOC 41), *Clerk* represents office and administrative support occupations (SOC 43), *Service* represents service and related occupations (SOC 33-39), *Agriculture* represents farming, fishing, and forestry occupations (SOC 45), and *Production* represents production, maintenance, construction, and transportation occupations (SOC 47-53).

[1] See Michaels, Page, and Whited (2016) for a recent example of using ReferenceUSA to improve the matching between BLS establishments and Compustat firms.

III. Extended Model

The simple technology-switching model in the main text makes several simplifying assumptions to show the core mechanism clearly. First, the model assumes that each firm is essentially a single project. Hence, the firm's *RShare* is either zero if the firm is automated or $\frac{c_R}{c_R+c_N}$ if the firm is unautomated. In the data, firms' *RShare* is a much more continuous variable. Second, the model excludes growth options by assuming that firms' production scale cannot be expanded or reduced. Hence, investment in this model is induced solely by countercyclical technology switching, while investment in general is very procyclical. Third, the model setup implies a nonstationary economy in terms of firms' *RShare*, since after a sufficient length of time, all firms switch from being unautomated to automated.

As an example to extend this model to capture additional features of the real world, I embed this technology-switching model in a production-based model setting. In this extended model, I follow the setup in Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), and Kogan and Papanikolaou (2014) by assuming that each firm has multiple projects and the firm can increase the number of projects by adopting new projects. The cash flows of each project are subject to aggregate-, firm-, and project-level shocks. The only new ingredient in this extended model, compared to the literature, is that there are two types of projects—automated and unautomated projects, just like the firms in the simple model. Due to idiosyncratic shocks, firms differ from each other in the number of automated and unautomated projects, making *RShare* vary continuously in the cross-section. Firms' exercise of their growth options (to adopt new projects) is subject to the net-present-value rule and thus is procyclical. The stationarity of the economy in terms of firms' *RShare* is achieved by imposing a mechanism for the exercise of growth options. In particular, I assume that building a new automated project takes more time (to adapt to the new technology) than building a new unautomated project. This assumption makes the firm prefer to adopt a new unautomated project to a new automated project when the firm is doing extremely well. In equilibrium, while existing unautomated projects are switched, new unautomated projects are undertaken, resulting in a stationary distribution of the two types of projects. Finally, I calibrate this extended model and support the model's quantitative fit with the data.

A. Technology

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

A.1. Projects

Each firm owns a finite number of individual projects. Firms create projects over time through investment, and projects expire randomly.[2] The cash flows generated by project j of firm i at time t are given by

$$A_{i,j,t} = e^{x_t + z_{i,t} + \epsilon_{j,t}}, \tag{IA.1}$$

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

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

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

$$da_{i,j,t} = -\theta a_{i,j,t} dt + \sigma_a dB_t, \tag{IA.3}$$

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

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

simplicity unless otherwise indicated.

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

A project's routine tasks can be performed by either fixed units of routine-task labor or fixed units of machines. If the firm hires routine-task labor, it pays a total wage of c_R per unit of time, and the project starts producing immediately. Production incurs a fixed cost of f per unit of time. I refer to projects using routine-task labor as *unautomated projects*. If the firm invests in machines, the firm pays I_M at the initiation date, but it takes the firm T units of time to adapt the technology embodied in the machines for its project, during which time the project does not generate any cash flows.[3] After the first T periods, the project starts generating cash flows and incurs a fixed cost of f per unit of time. Using machines does not incur additional fixed costs.[4] I refer to projects using machines as *automated projects*. All capital, once purchased, has zero resale value.

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

$$\pi_U(t) = A_t - c_R - c_N - f, \tag{IA.4}$$

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

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

A.2. Firm Dynamics

Given that each project uses a fixed amount of input factors, changes in a firm's capital and labor in the model are represented by changes in the *number* of the firm's unautomated and automated projects. Such changes are assumed to arise for one of three reasons. First,

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

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

at any point in time, projects can expire independently at a rate of δ. Second, following Kogan and Papanikolaou (2014), a new project can exogenously become available to the firm according to a Poisson process with an arrival rate of λ. At the time of arrival, the project-specific shock of the new project is at its long-run average value, that is, $\epsilon_t = 0$. Such investment opportunities cannot be postponed or preserved. If the firm decides to undertake the new project, it can choose to initiate either an unautomated or an automated project.

Third, a firm can endogenously switch its existing projects' type at any time. If the firm decides to switch a project from unautomated to automated, it lays off the project's routine-task labor and invests I_M in machines. I assume that technology has evolved to a stage such that automating unautomated projects is profitable. That is, I assume that I_M is significantly lower than the present value of all future wages paid to routine-task labor, $I_M \ll \frac{c_R}{r+\delta}$.[5] For simplicity, I assume that the process of the project-specific shock is not affected after a project's type is switched. Given that machines have zero resale value and routine-task labor is significantly more costly than machines, switching from automated projects to unautomated projects is never optimal.[6]

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

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

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

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

B. *Valuation*

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

$$\frac{d\Lambda_t}{\Lambda_t} = -rdt - \sigma_\Lambda dB_{xt}, \tag{IA.7}$$

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

B.1. *The Value of Automated Projects*

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

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

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

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

$$\begin{aligned} A_{t+s} &= A_t^{e^{-\theta s}} e^{\int_0^s \sigma_a e^{\theta(u-s)} dB_u} \\ \Lambda_{t+s} &= \Lambda_t e^{(-r - \frac{1}{2}\sigma_\Lambda^2)s - \sigma_\Lambda B_{xs}}, \end{aligned} \tag{IA.9}$$

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

$$\begin{aligned} V_A(t_0;t) &= E_t \int_0^\infty e^{-\delta s} \frac{\Lambda_{t+s}}{\Lambda_t} \left[\mathbb{1}_{(t+s > t_0 + T)}(A_{t+s} - f) - c_N\right] ds \\ &= E_t \int_{t'}^\infty A_t^{e^{-\theta s}} e^{v_s} ds - \frac{c_N + e^{-(r+\delta)t'} f}{r+\delta}, \end{aligned} \tag{IA.10}$$

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

$$E(v_s) = (-\delta - r - \frac{1}{2}\sigma_\Lambda^2)s$$
$$Var(v_s) = \sigma_\Lambda^2 s - \frac{2\sigma_x\sigma_\Lambda}{\theta}\left(1 - e^{-\theta s}\right) + \frac{\sigma_a^2}{2\theta}\left(1 - e^{-2\theta s}\right). \tag{IA.11}$$

Exchanging the expectation operator and the integral operator in (IA.10) using Fubini's Theorem, and using the log-normal property of e^{v_s}, we have

$$\begin{aligned} V_A(t_0; t) &= \int_{t'}^{\infty} A_t^{e^{-\theta s}} e^{E(v_s) + \frac{1}{2}Var(v_s)} ds - \frac{c_N + e^{-(r+\delta)t'} f}{r+\delta} \\ &= \int_{t'}^{\infty} A_t^{e^{-\theta s}} e^{g(s)} ds - \frac{c_N + e^{-(r+\delta)t'} f}{r+\delta}, \end{aligned} \tag{IA.12}$$

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

B.2. The Value of Unautomated Projects

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

$$V_U(t) = V_U^{AP}(t) + V_U^{SO}(t). \tag{IA.13}$$

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

$$\begin{aligned} V_U^{AP}(t) &= E_t \int_0^{\infty} e^{-\delta s} \frac{\Lambda_{t+s}}{\Lambda_t} \pi_U(t+s) ds \\ &= \int_0^{\infty} A_t^{e^{-\theta s}} e^{g(s)} ds - \frac{c_R + c_N + f}{r+\delta}. \end{aligned} \tag{IA.14}$$

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

$$V_U^{SO}(t) = \text{Payoff}(t+\tau)\hat{\mathbb{E}}_t[e^{-(r+\delta)\tau}], \tag{IA.15}$$

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

$$\begin{aligned}\text{Payoff}(t) &= V_A(t;t) - V_U^{AP}(t) - I_M \\ &= \frac{c_R + f[1-e^{-(r+\delta)T}]}{r+\delta} - I_M - \int_0^T A_t^{e^{-\theta s}} e^{g(s)} ds \\ &= P(A_t).\end{aligned} \tag{IA.16}$$

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

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

$$\frac{d\left[P(A^*)O(A_t, A^*)\right]}{dA^*} = 0 \qquad \forall A_t \geq A^*, \tag{IA.17}$$

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

Proof: Given that the payoff of exercising the switching option is monotonically decreasing in A_t (see equation (IA.16)) and also that the process of A_t exhibits positive serially correlation, we know that the optimal exercise of the switching option is when A_t falls below a certain threshold A^* (see Dixit and Pindyck (1994) section 4.1.D).

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

$$\begin{aligned}\frac{d\hat{\mathbb{P}}}{d\mathbb{P}} &= \frac{\Lambda_t}{\Lambda_0} e^{rt} \\ &= \exp\left(-\sigma_\Lambda B_{xt} - \frac{1}{2}\sigma_\Lambda^2 t\right),\end{aligned} \tag{IA.18}$$

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

$$d\hat{a}_t = -\theta \hat{a}_t dt + \sigma_a d\hat{B}_t, \tag{IA.19}$$

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

$$\begin{aligned} &\hat{E}_t[e^{-(r+\delta)\tau}] \\ &= \exp\left\{ \frac{\left[\left(\log A_t + \frac{\sigma_\Lambda \sigma_x}{\theta}\right)^2 - \left(\log A^* + \frac{\sigma_\Lambda \sigma_x}{\theta}\right)^2\right]\theta}{2\sigma_a^2} \right\} \frac{D_{-(r+\delta)/\theta}\left[\left(\log A_t + \frac{\sigma_\Lambda \sigma_x}{\theta}\right)\sqrt{\frac{2\theta}{\sigma_a^2}}\right]}{D_{-(r+\delta)/\theta}\left[\left(\log A^* + \frac{\sigma_\Lambda \sigma_x}{\theta}\right)\sqrt{\frac{2\theta}{\sigma_a^2}}\right]} \quad \text{(IA.20)} \\ &= O(A_t, A^*), \end{aligned}$$

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

$$D_x(z) = 2^{x/2}\sqrt{\pi}\exp\left(-\frac{z^2}{4}\right)\left\{\frac{1}{\Gamma\left(\frac{1-x}{2}\right)}H\left(-\frac{x}{2}, \frac{1}{2}; \frac{z^2}{2}\right) - \frac{\sqrt{2}z}{\Gamma\left(-\frac{x}{2}\right)}H\left(\frac{1-x}{2}, \frac{3}{2}; \frac{z^2}{2}\right)\right\}, \quad \text{(IA.21)}$$

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

$$H(\alpha, \gamma; z) = \sum_{n=0}^{\infty} \frac{(\alpha)_n}{(\gamma)_n} \frac{z^n}{n!} \quad \text{(IA.22)}$$

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

COROLLARY 1 (Cross-section of investment for technology switching): *Holding all else equal, a firm with a high RShare invests more in machines than a firm with a low RShare if the economy experiences a negative shock, that is,* $dx_t < 0$.[7]

Proof: This follows directly from Proposition 1.

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

Proof: This follows directly from Proposition 1.

[7]"Holding all else equal" in this corollary means that we are comparing two firms with the same number of projects and the same set of cash flows for their projects. The only difference is that the high-*RShare* firm has more unautomated projects than the other firm.

Finally, the value of the unautomated project is

$$V_U(t) = \int_0^\infty A_t^{e^{-\theta s}} e^{g(s)} ds - \frac{c_R + c_N + f}{r + \delta} + P(A^*)O(A_t, A^*). \tag{IA.23}$$

B.3. The Value of Growth Opportunities

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

The optimal exercise of switching options indicates that firms prefer undertaking new automated projects over undertaking new unautomated projects if $A_t < A^*$.[8] Let A^{**} be the threshold for firms to undertake a new project. The term A^{**} is determined by making the investment in the new project a zero-NPV project, that is, A^{**} is the solution to

$$V_A(t; t) - I_M - I = 0 \tag{IA.24}$$

or to

$$V_U(t) - I = 0. \tag{IA.25}$$

I summarize these results in the following proposition.

PROPOSITION 2 (Optimal exercise of growth options): *A firm optimally undertakes a new project when the cash flows of the new project, $A_t = e^{x_t + z_t + 0}$, are above a threshold A^{**}, where A^{**} is the minimum of the solutions to equations* (IA.24) *and* (IA.25).

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

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

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

Proof: This follows directly from Proposition 2.

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

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

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

Proof: This follows directly from Proposition 2.

The intuition of this corollary is straightforward. Because new unautomated projects can start generating cash flows more quickly than new automated projects, they are preferable to be undertaken for expansions when firms are doing well.[9] This corollary has two implications in the model. First, it helps generate a stationary distribution of the two types of projects, since in equilibrium, while existing unautomated projects are switched to automated ones, new unautomated projects are also undertaken.

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

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

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

$$\begin{aligned} PVGO(t) &= E_t \int_{s=0}^{\infty} \lambda \frac{\Lambda_{t+s}}{\Lambda_t} \max\left[V_U(t+s) - I, V_A(t+s; t+s) - I_M - I, 0\right] ds \\ &= G(x_t, z_t). \end{aligned} \tag{IA.26}$$

[9]This argument is consistent with Berger (2012), who argues that firms grow "fat" during booms and streamline their production during recessions.

B.4. Firm Value

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

$$V(t) = \sum_{l=1}^{n_{U,t}} V_{U,l}(t) + \sum_{k=1}^{n_{A,t}} V_{A,k}(t_k; t) + PVGO(t). \tag{IA.27}$$

C. Firm Risk

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

$$\beta = -\frac{\mathrm{Cov}\left(\frac{dV}{V}\frac{d\Lambda}{\Lambda}\right)}{\mathrm{Var}\left(\frac{d\Lambda}{\Lambda}\right)}. \tag{IA.28}$$

From equation (IA.27), we know that a firm's beta is the weighted average of the betas of its existing projects and the beta of its growth opportunities,

$$\beta_f = \sum_{l=1}^{n_U} \frac{V_{U,l}}{V}\beta_{U,l} + \sum_{k=1}^{n_A} \frac{V_{A,k}}{V}\beta_{A,k} + \frac{PVGO}{V}\beta_{PVGO}. \tag{IA.29}$$

Given that multiple channels drive the cross-sectional comparison in betas between firms with a high and a low *RShare*, I calibrate the model in the next section to examine whether the switching options channel is a dominating channel under economically reasonable parameters.

D. Calibration

I simulate the model to examine whether the switching option channel is powerful enough to generate lower risk premia for high-*RShare* firms in the cross-section under economically reasonable parameters. In addition, this test helps shed light on whether the predictability of *RShare* on stock returns is robust to the dynamic setting in which *RShare* evolves endogenously.

To conduct the calibration, I take the following steps. First, I discretize the continuous model. Second, I obtain the values of parameters by matching several economic moments. Third, I plug the parameter values into the model and simulate the model to generate stock returns for five portfolios sorted on the share of routine-task labor.

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

$$\begin{aligned} \Lambda_{t+\Delta t} &= \Lambda_t e^{(-r-\frac{1}{2}\sigma_\Lambda^2)\Delta t - \sigma_\Lambda \sqrt{\Delta t}\xi_{xt}} \\ e^{x_{t+\Delta t}} &= \left(e^{x_t}\right)^{e^{-\theta\Delta t}} e^{\sigma_x \sqrt{\frac{1-e^{-2\theta\Delta t}}{2\theta}}\xi_{xt}} \\ e^{z_{t+\Delta t}} &= \left(e^{z_t}\right)^{e^{-\theta\Delta t}} e^{\sigma_z \sqrt{\frac{1-e^{-2\theta\Delta t}}{2\theta}}\xi_{zt}} \\ e^{\epsilon_{t+\Delta t}} &= \left(e^{\epsilon_t}\right)^{e^{-\theta\Delta t}} e^{\sigma_\epsilon \sqrt{\frac{1-e^{-2\theta\Delta t}}{2\theta}}\xi_{\epsilon t}}, \end{aligned} \tag{IA.30}$$

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

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

Profits in each period are thus

$$\begin{aligned} \pi_A(t) &= (A_t - c_N - f)\Delta t \\ \pi_U(t) &= (A_t - c_R - c_N - f)\Delta t. \end{aligned} \tag{IA.31}$$

The value of V_A and V_U^{SO} can be easily calculated based on the analytical functional forms. I calculate A^* by searching a large space of A_t.

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

$$V_t = d_t + E(\frac{\Lambda_{t+\Delta t}}{\Lambda_t} V_{t+\Delta t}), \tag{IA.32}$$

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

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

$$PVGO_t = \frac{\lambda \Delta t}{J} \sum_{j=1}^{J} \sum_{n=1}^{\infty} PVGO_{j,n}, \tag{IA.33}$$

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

Panel A of Table IAXIII summarizes the parameter choices. My model setup shares many features with Kogan and Papanikolaou (2014), who also develop a model at the project level. Hence, I adopt assumption of the parameter values used by Kogan and Papanikolaou (2014) as possible. Specifically, I adopt the parameter values in Kogan and Papanikolaou (2014) for the volatilities of x_t, z_t, and ϵ_t, the rate of mean-reversion, the risk-free rate, and the project obsolescence rate.[10] The required time for technology adoption is absent in the model of Kogan and Papanikolaou (2014). I thus set the required time to be three quarters following the time-to-build literature (e.g., Kydland and Prescott (1982) find that a reasonable range for the average construction period is three to five quarters).

Given that Kogan and Papanikolaou (2014) have two factors in their pricing kernel while my model only has one, I choose the price of risk to match the equal-weighted aggregate risk premium. Because I assume a constant price of risk in my stochastic discount factor for tractability, I need an unrealistically high value for the price of risk to match the risk premium.[11] In addition, my model has a much simpler setting for growth opportunities compared to the model of Kogan and Papanikolaou (2014), and thus I set the project arrival rate to match the aggregate dividend growth rate.

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

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

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

initiation, I, and the cost of machines per automated project, I_M, are chosen to match the correlation between gross investment and GDP growth. See Panel B of Table IAXIII for the moments.

Plugging these parameter values into equations (IA.17), (IA.24), and (IA.25), we obtain the optimal thresholds for exercising switching options and growth options. Under these parameter values, $A^* = 0.75$ and $A^{**} = 0.81$, while the 40th, 50th, and 60th percentiles of A_t are 0.63, 1.00, and 1.58, respectively.

Table IAXIII
Parameter Values and Calibration Moments

This table presents the parameter values used in the calibration of the model.

Panel A: Parameter Values		
Parameters	Symbol	Value
Technology		
Volatility of aggregate shock	σ_x	0.13
Volatility of firm-specific shock	σ_z	0.15
Volatility of project-specific shock	σ_ϵ	1.25
Rate of mean reversion	θ	0.30
Project		
Operating cost except for labor compensation	f	1.25
Compensation for nonroutine-task labor	c_N	0.25
Compensation for routine-task labor	c_R	0.35
Investment for project initiation	I	3.50
Investment in machines per automated project	I_M	0.10
Required time for technology adoption	T	0.75
Project obsolescence rate	δ	0.10
Project arrival rate	λ	12
Stochastic discount factor		
Risk-free rate	r	0.03
Price of risk of aggregate shock	σ_Λ	1.30

Panel B: Calibration Moments		
Moments	Data	Model
Aggregate economic moments		
Mean of aggregate dividend growth	0.02	0.02
Volatility of aggregate dividend growth	0.12	0.18
Aggregate share of routine-task labor	0.14	0.14
Aggregate labor share in GDP	0.55	0.24
Correlation between gross investment and GDP Growth	0.48	0.49
Correlation between gross hiring and GDP Growth	0.74	0.59
Asset pricing moments		
Mean of equal-weighted aggregate risk premium	0.14	0.15
Volatility of equal-weighted aggregate risk premium	0.26	0.14

Using the above parameter choices, I simulate the model at a monthly frequency ($dt =$

1/12) for 1,000 firms over 1,200 periods. I drop the first 600 periods to eliminate dependence on initial values. I simulate 100 times and calculate the standard errors across simulations.

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

Table IAXIV

Five Portfolios Sorted on *RShare* using Model-Simulated Data

This table reports asset pricing tests for five portfolios sorted on share of routine-task labor (*RShare*) using model simulated data. The model is simulated at a monthly frequency for 1,000 firms over 1,200 periods for 100 rounds. The first 600 periods are dropped to eliminate dependence on initial values. Excess returns and CAPM alphas are annualized by multiplying by 12 and are reported in percentages. *, **, and *** indicate significance level of 10%, 5%, and 1%, respectively.

	L	2	3	4	H	H−L
			1. Excess Returns			
$E[R] - r_f$ (%)	17.02***	16.07***	14.91***	14.74***	14.56***	−2.46***
	(1.71)	(1.65)	(1.55)	(1.49)	(1.46)	(0.12)
			2. Unconditional CAPM			
MKT β	1.13***	1.11***	1.02***	0.96***	0.95***	−0.17***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α (%)	−0.14	−0.11	−0.13	−0.19	−0.09	0.04
	(0.10)	(0.11)	(0.11)	(0.10)	(0.10)	(0.15)
R^2	0.99	0.99	0.99	0.99	0.99	0.53

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