Replication of Key Findings in

"*Labor-Technology Substitution: Implications for Asset Pricing*"

using Publicly Available Industry-Level Data

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In this mimeo, I construct the share of routine-task labor at detailed industry level (*iRShare*) to proxy for firms' RShare in Zhang (2019). I then replicate two key findings in Zhang (2019). First, betas decrease monotonically for both equal-weighted and value-weighted portfolios sorted by *iRShare* within broad industry sectors. Second, when GDP growth is low, firms with a high *iRShare* invest more in machines (but not in other capital) compared to other firms in the same sector with a low *iRShare*. The full *iRShare* series can be downloaded at `https://www.MiaoBenZhang.com/`.

Disclaimer: This mimeo is indented to explore how the industry-level measure of RShare can generate qualitatively similar results to those using firm-level RShare in Zhang (2019). The statistics presented here are NOT intended to be the same as the statistics in Zhang (2019). A full replication code that requires accessing to the BLS microdata is available in the *Journal of Finance* website.

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I. Constructing *iRShare*

The Bureau of Labor Statistics provides publicly available data on occupational employment and wages for detailed industries at https://www.bls.gov/oes/tables.htm. Industries in the data are classified at the 3-digit Standard Industrial Classification (SIC) before 2002 and at the 4-digit North American Industry Classification System (NAICS) after 2002 (including 2002). These industry-level data are constructed by the BLS using establishment-level microdata that are used in Zhang (2019).[1]

Zhang (2019) details the procedure of computing a time-varying classification of occupations into routine-task labor.[2] An industry's share of routine-task labor (*iRShare*) is the proportion of the industry's total labor costs paid to routine-task labor, constructed following equation (19) of Zhang (2019). This procedure results in an *iRShare* measure for about 320 industries each year from 1990 to 2018. Table I shows the top 10 industries and bottom 10 industries with the highest and least share of routine-task labor as of 2014 (the last year of data used in Zhang (2019)). The full *iRShare* series can be downloaded at https://www.miaobenzhang.com/.

II. Features of *iRShare*

Compared to existing measures of routine-task labor, three features of *iRShare* are:

1. *iRShare* is based on a **time-varying classification of routine-task labor** developed by Zhang (2019), while existing measures of routine-task labor are fixed

[1] As detailed in Zhang (2019), the OES data do not have wage information before 1998. Hence, for years before 1998, I estimate the hourly wages from the Census Current Population Survey Merged Outgoing Rotation Groups (CPS-MORG). See the Internet Appendix of Zhang (2019) for the detailed procedure of this wage imputation.

[2] That is, I rank all workers in the economy based on their routine-task intensity in *each year* and classify the top quintile workers' as routine-task labor. The national occupational employment during 1997-2018 can be downloaded from the BLS OES website. During 1988-1995, OES surveys each industry in every three years. Hence, I stack the current year and the past two years of data to proxy for the total labor force in the economy for each year during 1990-1995 as in Zhang (2019). OES website does not provide data for 1996. I thus use industries' *iRShare* in 1995 to proxy for their *iRShare* in 1996 following Donangelo (2014).

for an occupation over time largely due to their reliance on the Census Decennial data (see Autor et al. (2003), Autor and Dorn (2013), and many others). Hence, when an occupation that is not replaceable by technology in early years becomes replaceable in later years as technology progresses, existing measures cannot account for such technology progress.[3]

2. *iRShare* is constructed using the OES data which classify industries using the SIC 3-digit and NAICS 4-digit classifications. Different from the Census industry codes, the SIC and NAICS industry codes are frequently used in business databases such as the Compustat and CRSP databases. This makes *iRShare* easier to be matched to firm-level databases.

3. *iRShare* is updated yearly from 1990 to 2018, providing a timely high frequency measure for an industry's share of routine-task labor.

III. *iRShare* and Firm Risk

I examine the CAPM beta of portfolios sorted by *iRShare*. I compare detailed industries with different *iRShare* within broad industry sectors to ensure that *iRShare* does not simply reflect the heterogeneous business models across industry sectors, such manufacturing versus services. For the 1990-2001 sample, I use the SIC 1-digit division to classify 10 industry sectors. For the 2002-2014 sample, I definition a similar classification for industry sectors by crosswalking NAICS 4-digit codes to SIC 3-digit codes. I require firms to have at least two years of data in the Compustat database to avoid look-ahead bias (Fama and French (1993)). I further remove financial firms (SIC 6000-6999) and micro-cap firms defined as firm size below NYSE 5-percentile as of June of the year. Table II shows that while *iRShare* quadrupled from 7.96% for

[3]Few examples of occupations in the OES data that changed from non-routine to routine based the time-varying classification of routine-task labor during 2002-2018 are "Radio and Television Announcers", "Bookkeeping, Accounting, and Auditing Clerks" and "Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders".

the low-*iRShare* portfolio to 32.79% for the high-*iRShare* portfolio, the betas *decreased* more than 20% in both equal-weighted and value-weighted portfolios.

IV. *iRShare* and Firm Response to Aggregate Shocks

The main mechanism in Zhang (2019) is that firms with a high share of routine-task labor hold a real option to replace their routine-task workers with machines during bad times. Given that the opportunity cost of such replacement (e.g., temporary shut down of plants for restructuring) is pro-cyclical, this replacement option hedges firms value for high-*RShare* firms, making these firms less risky than low-*RShare* firms. The results in the above section confirms this prediction by showing that firms in high-*iRShare* industries have lower exposure to systematic risks than firms in the same broad sector but from low-*iRShare* industries. To examine the mechanism, in this section, I run a regression analougous to equation (22) in Zhang (2019) as following:

$$I^M_{f,i,t} = a_0 + b_1 iRShare_{i,t-1} + b_2 Shock_t + b_3 iRShare_{i,t-1} \times Shock_t + F_{Firm} + F_{Sector \times Year} + \epsilon_{f,t}, \tag{1}$$

where $I^M_{f,t}$ is firm f's investment in machines in year t (see details in Zhang (2019)), $Shock_t$ is the GDP shock in year t, and $iRShare_{i,t-1}$ is the firm's belonged industry's share of routine-task labor in year $t-1$. F_{Firm} and $F_{Sector \times Year}$ are firm and sector-year fixed effects, respectively. Standard errors are clustered by firms. From a difference-in-differences perspective, this regression aims to examine how firms with high and low *iRShare*s respond to unfavorable GDP shocks in terms of technology investment. Consistent with the mechanism that high-*iRShare* firms invest more in technology (to replace routine-task labor) when facing unfavorable macroeconomic shocks than low-*iRShare* firms, Column (1) of Table III shows a significant and negative estimation of b_3. Column (2) of Table III presents results of a placebo test in which we do not see significant differences in high-*iRShare* and low-*iRShare* firms' responses to GDP shocks in terms of investing in capital other than machines.

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Table I
Industries with Highest and Lowest *iRShare*

This table reports the 10 industries with the highest share of routine-task labor (*iRShare*) and the 10 industries with the lowest *iRShare* as of 2014.

NAICS	Industry Title	*iRShare*
	Panel A: Top 10 Industries with Highest *iRShare*	
4451	Grocery Stores	65.65%
4471	Gasoline Stations	64.88%
3361	Motor Vehicle Manufacturing	53.13%
3131	Fiber, Yarn, and Thread Mills	52.93%
3116	Animal Slaughtering and Processing	50.53%
4453	Beer, Wine, and Liquor Stores	50.44%
4452	Specialty Food Stores	48.31%
3117	Seafood Product Preparation and Packaging	46.14%
7225	Restaurants and Other Eating Places	44.45%
4529	Other General Merchandise Stores	41.27%
	Panel B: Bottom 10 Industries with Lowest *iRShare*	
4911	Postal Service	1.09%
4854	School and Employee Bus Transportation	1.19%
5172	Wireless Telecommunications Carriers (except Satellite)	1.27%
4879	Scenic and Sightseeing Transportation, Other	1.38%
4811	Scheduled Air Transportation	1.60%
5232	Securities and Commodity Exchanges	2.11%
4921	Couriers and Express Delivery Services	2.20%
5112	Software Publishers	2.32%
5415	Computer Systems Design and Related Services	2.32%
5417	Scientific Research and Development Services	2.39%

Table II
CAPM Betas and *iRShare*

This table reports average *iRShare* and CAPM betas for five portfolios sorted on their industry-level share of routine-task labor ($iRShare$). At the end of each June, detailed industries within each industry sector are sorted into five portfolios based on their *iRShare*. Newey and West (1987) standard errors, reported in parentheses, are estimated with four lags. All 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: Average iRShare						
iRShare	7.96%	12.78%	16.78%	21.85%	32.79%	24.83%
Panel B: Betas for Equal-Weighted Portfolios						
MKT β	1.31***	1.19***	1.15***	1.09***	1.00***	−0.31***
	(0.05)	(0.04)	(0.03)	(0.06)	(0.06)	(0.08)
α (%)	0.24	−1.25	2.33	0.82	0.31	0.07
	(2.95)	(2.32)	(1.97)	(2.15)	(2.13)	(3.17)
Panel C: Betas for Value-Weighted Portfolios						
MKT β	1.05***	1.01***	0.93***	0.97***	0.85***	−0.20**
	(0.05)	(0.03)	(0.02)	(0.04)	(0.04)	(0.08)
α (%)	−0.11	0.06	2.64**	−0.08	−0.41	−0.30
	(1.45)	(1.33)	(1.13)	(1.17)	(1.46)	(2.45)

Table III
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 in industries with different shares of routine-task labor, *iRShare*. The sample includes firms that generate the results in Table II during 1990-2014. *Investment in Machines* is the growth rate of machinery and equipment capital from $t-1$ to t. *Investment in Other Capital* is the growth rate of property, plant, and equipment excluding machinery and equipment from $t-1$ to t. See more details in Zhang (2019). *Shock* is the annual GDP growth rate from $t-1$ to t. All standard errors are clustered at the firm level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.	Investment in Machines	Investment in Other Capital
	(1)	(2)
$iRShare_{t-1} \times Shock_t$	-1.84^{***}	-0.88
	(0.64)	(0.80)
$iRShare_{t-1}$	0.18^{***}	0.15^{***}
	(0.04)	(0.06)
Firm FE	Yes	Yes
Sector× Year FE	Yes	Yes
Observations	36,346	36,346
Adjusted R^2	0.32	0.26