Embodied and Disembodied Capital in Energy Conservation: the Case of Chinese Industry

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Abstract

This paper quantitatively investigates the role of embodied and disembodied technology change in energy conservation in Chinese industries from 1997 to 2004. By explicitly incorporating both embodied and disembodied technology change into a Dynamic Stochastic General Equilibrium (DSGE) model, we are able to identify and separate the impact of the two types of technology change. Further, the role of embodied technology is estimated through indirect inference, so the DSGE model is able to reproduce the long-run price elasticity that directly observed from the firm-level data. Our estimation shows that embodied disembodied technology contributes to 70-75% of energy conservation in Chinese industrial firms, which indicates that embodied technology change plays a much important role in energy conservation in Chinese industries from 1997 to 2004.

1 Introduction

This paper quantitatively investigates the role of embodied and disembodied technology change in energy conservation in Chinese industries from 1997 to 2004. How to best reduce energy intensity in China is one of the most important questions on today's global environment and policy agenda. It has become especially relevant as China has quickly risen to the top ranks in global energy demand over the past few years. China has been the largest global energy consumer since 2010; in 2013

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it accounted for 22.4% of the world's total energy consumption (BP statistics, 2014). Especially, China has been the world's leading coal producer and consumer in recent years, it accounts for close to half of the global coal consumption, and it is the world's second-largest oil consumer behind the United States (EIA, 2014). As a consequence, China is an important factor in world energy-related CO_2 emissions, releasing 8,715 million metric tons of CO_2 in 2011, accounting for 25.4% of global emission (IEA, 2013). Since 2006, China's CO_2 emissions have surpassed U.S. as the world's largest CO_2 emitter in the world (World Bank, 2014).

Macroeconomists have long believed that technology change is a key determinant of economic growth. The question that we intend to ask is how important is embodied technology in achieving energy conservation or reducing energy intensity (total energy consumption over output) in China. The embodied technology is characterized by an increase in productivity or a decrease in energy intensity of new vintages of capital relative to old vintages. Examples abound: LED lights, hybrid and electric vehicles, etc. In contrast, the neoclassical growth model in macroeconomics focuses disembodied or neutral technology change, as for example in Solow model. Disembodied technological progress allows all goods to be produced more efficiently.

The purpose of this paper is to examine the role of embodied and disembodied technology change, and more specifically, to measure quantitatively their contribution to achieving energy conservation. Specifically, we model the disembodied technology change as putty-putty investment, which assumes that capital are flexible and homogeneous. In contrast, we model the embodied technology change as putty-clay investment, which exhibits rigidity of energy intensity in new investment, and energy intensity of every vintage of capital is optimally chosen by firms. We incorporate both disembodied and embodied technology change, or by incorporating both putty-putty and putty-clay investment, into a Dynamic Stochastic General Equilibrium (DSGE) model. Through indirect inference, the estimated DSGE model is able to reproduce the facts that observed directly from the firm-level data. This allows us to quantitatively measure the contribution of embodied technology change. The analysis concludes that 70-75% of energy conservation can be accounted for embodied technology change in Chinese industries from 1997 to 2004.

The paper is organized as follow: section 2 presents the stylized facts, basically the long-run price elasticity of firms, using a unique panel data recording firm-level energy consumption from 1997 to 2004. In section 3, we develop a dynamic stochastic general equilibrium (DSGE) model, explicitly incorporating disembodied and embodied technology change. Section 4, we uncover the structural parameters in the DSGE model, which is able to re-produce the long-run price elasticity that are presented in section 2. Conclusions are drawn in section 6.

2 Empirical Facts

2.1 Data set and variables

The firm-level data used in this paper are a subset of the Large and Medium-sized Enterprises (LME)[1] data set collected by China's National Bureau of Statistics (NBS) from year 1997 to 2004. It provides financial and economic variables as well as energy consumption variables. Specifically, the energy data includes the amount of consumption, value of purchases and quantity of purchase for 21 energy types.

The sample used in this analysis is an unbalanced panel, consisting of approximately 35,000 firms. I clean the data set and exclude outliers by the following criteria. First, observations for which key financial variables (such as total assets, net value of fixed assets, sales, and gross value of industrial output) are missing are dropped. Second, observations for which key classifications have inconsistent number of digits (i.e., the regional code should be 6 digits, the ownership code should be 3 digits, and the industrial code should be 4 digits) are dropped. Further, I delete observations according to the basic rules of generally accepted accounting principles if any of the following are true: (1) liquid assets are higher than total assets; (2) total fixed assets are larger than total assets; (3) the net value of fixed assets is larger than total assets; (4) the firm's identification number is missing. Last, two key variables,energy intensity and energy price, exhibit extremely large values. These unreasonably large values might be due to mis-reporting or measurement errors. Therefore, the observations with largest 1% value of energy intensity and energy prices are trimmed off.

After preparing the data, there are 35,377 observations over the period 1997-2004. Table 1 compares the levels of energy consumption, sales revenue, total assets and employment with the full population of industry firms,[2] and Large and Medium-sized Enterprises in year 2004. The firms in

[1] Large and Medium-sized Enterprises are industrial enterprises with annual sales over 30 million yuan, total assets over 40 million yuan and total employment over 300 persons.

[2] In 2004 NBS did a survey of all industry enterprises, which include above scale enterprises (all state-owned enterprises and non-state-owned enterprise with sales more than 5 million yuan) and below scale enterprieses.Therefore the number of all industrial enterprise is large.

this sample consist of about 56% of all industrial consumption in 2004.

Two key variables of interest, energy intensity and the real energy price, are constructed in the following way. First, energy intensity is constructed as the ratio of overall energy consumption to the real output. Real output corresponds to the variable gross value of industrial output (GVIO) at constant price level. Overall energy consumption is measured in physical quantities as tons of standard coal equivalence (SCE). Firms report their amount of consumption, value of purchase and quantity of purchase for 21 energy types. The NBS weights the individual energy types to provide a measure of overall energy consumption. The weights are firm-specific conversion coefficients for those 21 energy types. Second, real energy prices are constructed as the nominal energy price divided by the output price; both prices are measured at the firm-level. The nominal energy price is calculated as the total value of purchases for 21 energy types divided by the total quantity of purchase, which is summed over 21 energy types. Each energy type is converted to standard coal equivalence by the conversion coefficients provided by the NBS.[3] The output price is calculated as GVIO at current price level divided by GVIO at its constant price level, the implicit output price deflators are provided by the NBS.

2.2 Estimation of long-run elasticity

This subsection estimates the long-run effect of price on energy intensity, for 3 types of firms: state-owned enterprises (SOEs), domestically owned non-SOEs (Non-SOEs), and foreign-funded firms (For). The long-run price elasticities tend to become more equal among SOEs, non-SOEs and foreign-funded firms. In particular, over the long-run, SOEs tend to be more responsive to rising energy prices by investing in new physical capital to improve their energy efficiency, while similar investment responsiveness does not hold for non-SOEs or foreign-funded firms.

The long-term price elasticity is estimated by including lagged energy prices into energy intensity equation. The long-run elasticity is estimated as follows:

$$Ln(\frac{EN_t}{Y_t}) = \beta_0 + \beta_1 Ln(P_E)_t + \beta_2 Ln(P_E)_{t-1} + \ldots + \beta_5 Ln(P_E)_{t-5} + controls + \varepsilon \qquad (1)$$

where the control variables include year dummies, industry and province dummies. The dependent

[3] The adoption coefficients for 21 types of energy are available from the author.

variable is log of energy intensity, which is the ratio of total energy consumption EN to the real output level Y. Right-hand side variables are log of real energy price P_E, and its lag terms. The lagged energy price terms intend to capture the dynamic effect of price on energy intensity. Equation (1) is estimated by three sub samples: SOEs, non-SOEs and foreign-funded firms separately, and the results are reported in Table 2 . The left panel of Table 2 corresponds to the estimation results for SOEs, the middle panel corresponds to non-SOEs, and the right panel is for foreign-funded firms. Longer lagged price terms were added, however they are not reported due to their coefficients are insignificant.

The coefficients in Table 2 are all significantly negative. The contemporaneous impact of energy price on energy intensity is larger than that of lagged energy prices, for all SOEs, non-SOEs and foreign-funded firms.

3 Model

3.1 Disembodied technology change (putty-putty model)

Disembodied technology is modeled by putty-putty investment, which follows the convention in neoclassic growth model. With the disembodied technology change only, the DSGE model is an extension of the classical business cycle model. Specifically, the model is described by a social planner's problem as follow:

$$\max_{\{C_t, L_t, EN_t, K_{t+1}\}_{t=0}^{\infty}} E_0\{\beta^t U(C_t, L_t)\}$$

subject to:

$$\begin{aligned} C_t + K_{t+1} - (1-\delta)K_t &= Y_t - P_t EN_t \\ Y_t &= [K_t^{\lambda} EN_t^{(1-\lambda)}]^{\alpha} L_t^{1-\alpha} \\ P_{t+1} - \bar{P} &= \rho(P_t - \bar{P}) + \varepsilon_{t+1} \end{aligned}$$

3.2 Embodied technology change

In this subsection, we described two model, both uses putty-clay investment. One model is described in Atkeson and Kehoe (1999), hereafter referred as putty-clay-AK model. The other model is from Chao Wei (2003), hereafter referred as putty-clay-CW model. Here we briefly describe their models for convenience.

3.2.1 Putty-clay investment without idiosyncratic productivity (AK model)

There exists a variety of differentiated capital goods with types indexed by $v \in V$, where V is a finite set contained in $[0, \infty)$. A unit of capital of type v provides capital service in production only in combination with $1/v$ units of energy. If k units of capital of type v are combined with e units of energy where $e > k/v$, then the energy in excess of k/v is wasted. If $e, k/v$, then capital in excess of ev is left idle. Capital services are then combined with labor to produce output. Use of $k(v)$ units of capital of type v, together with $e(v)$ units of energy and $n(v)$ units of labor yields

$$Y(v) = [\min(\frac{k(v)}{v}, e(v)) \cdot f(v)]^{\alpha} L(v)^{1-\alpha}$$

units of output, where $f(v) = v^{\alpha}$. $\min(\frac{k(v)}{v}, e(v))$ reflects that energy intensity of every vintage capital is fixed. The choice of $f(v) = v^{\alpha}$ indicates that the underlying production function is based on the standard Cobb-Douglas production function, which makes the models comparable.

The social planner's problem is as follow:

$$\max_{\{C_t, e_t(v), L_t(v), x_t(v), v\}} E_0\{\beta^t U(C_t, L_t)\}$$

subject to:

$$Y_t = \sum_v [\min(\frac{k_t(v)}{v}, e_t(v)) \cdot f(v)]^{\alpha} L_t(v)^{1-\alpha}$$

$$C_t + \sum_v x_t(v) \leq Y_t - P_t \sum_v e_t(v)$$

$$k_{t+1} = (1-\delta)k_t(v) + x_t(v)$$

$$e_t(v) \geq 0, L_t(v) \geq 0, x_t(v) \geq 0$$

$$\sum_v L_t(v) \leq 1$$

$$P_{t+1} - \bar{P} = \rho(P_t - \bar{P}) + \varepsilon_{t+1}$$

For the detail of this model, please refer to Atkeson and Kehoe (1999).

3.2.2 Putty-clay investment with idiosyncratic productivity (CW model)

In this subsection, the model not only uses putty-clay investment, but also incorporate the machine-level idiosyncratic productivity within a vintage. In AK model, all machines in a vintage capital share the same productivity, all the machines in a vintage is fully utilized or idled completely. However, in CW model, machines within a vintage are heterogeneous, characterized by vintages, capital-energy ratio k, energy-labor ratio e, and the value of the idiosyncratic productivity term θ_i. Specifically, the output in period t by machine i of vintage $t-j$ is

$$Y_{i,t}^{t-j} = \theta_{i,t-j} k_{t-j}^{\lambda\alpha} e_{t-j}^{\alpha} L_t^{t-j}$$

where

$$ln\theta_{i,t-j} \sim Normal(-\frac{1}{2}\sigma^2, \sigma^2) \text{ and } 0 \leq L_t^{t-j} \leq 1$$

here σ^2 is the variance. The mean correction term $-\frac{1}{2}\sigma^2$ implies that the mean of the idiosyncratic productivity, $\theta_{i,t-j}$, equals 1 .

The social planner problem is:

$$\max_{\{C_t, L_t, Q_t, En_t, k_t, e_t, z_t^{t-j}\}} E_0\{\beta^t U(C_t, L_t)\}$$

subject to:

$$C_t + k_t e_t Q_t = Y_t - P_t En_t$$

$$Y_t = \sum_{j=1}^{M} \{[1 - \Phi(z_t^{t-j} - \sigma)](1 - \delta_j) Q_{t-j} k_{t-j}^{\lambda\alpha} e_{t-j}^{\alpha}\}$$

$$L_t = \sum_{j=1}^{M} \{[1 - \Phi(z_t^{t-j})](1 - \delta_j) Q_{t-j}\}$$

$$En_t = \sum_{j=1}^{M} \{[1 - \Phi(z_t^{t-j})](1 - \delta_j) Q_{t-j} e_{t-j}\}$$

$$z_t^{t-j} = \frac{1}{\sigma}[ln(W_t + P_t e_{t-j}) - ln(k_{t-j}^{\lambda\alpha} e_{t-j}^{\alpha}) + \frac{1}{2}\sigma^2]$$

$$P_{t+1} - \bar{P} = \rho(P_t - \bar{P}) + \varepsilon_{t+1}$$

where $\Phi(\cdot)$ is PDF of a standard normal distribution.

For the detail of this model, please refer to Chao Wei (2003).

3.3 Model calibration and solution

For all 3 models, I calibrate the parameters before solving them. Table 3 summarizes the preference and technology parameter values which I will use in the models.

The time period is taken to be one year. The utility function is chosen as $U(C_t, L_t) = \frac{C_t^{1-\gamma}(1-L_t)^{\phi 1-\gamma}}{1-\gamma}$. The coefficient of the relative risk aversion γ is 1.5. The discount rate β equals 0.997 , and the depreciation rate δ equals 0.1. Those are consistent with Song et al. (2011). The leisure parameter ϕ is set to be 3. The leisure parameter ϕ is chosen so that households work about 23% of their time in the steady state.

The steady state values of the quantity and price variables are independent of γ. Together with ϕ, the parameter γ governs the inter temporal substitution of the consumption and labor supply across time. Holding ϕ fixed, a higher γ implies a lower inter temporal elasticity of substitution.

On the production side, λ is set to be 0.757 and α is set to be 0.689. Together they imply a labor share of income of 0.32, an energy share of income of 0.17, and a capital share of income of 0.52, which are the average factor shares from the firm-level data. The capital share 0.52 is consistent with Bai et al. (2006). The number of vintages, M, is set to be 3.

There is no prior estimate for the standard deviation of the idiosyncratic uncertainty, σ. For the calibration, σ is set to be 0.53, which implies that 80% of machines are in operation in the steady state. 80% capital utilization rate is close to IMF estimated utilization rate in China from 1997-2004 (IMF, 2012).

The process of energy price is assumed to follow an AR(1) process as described the models, and estimated directly from the firm-level data. Here I estimate the energy price process for state-owned enterprises (SOEs), domestic non-SOEs and foreign-funded firms individually, because the share of output produced by the putty-clay investment will be estimated individually for the three types of firms. Though it is difficult to have a prior on the serial correlation of energy price, the unconditional means of energy price for three types of firms, shown in the bottom of Table 3, are consistent with the facts documented in Tang (2015): SOEs face the lowest price, followed by domestic non-SOEs and foreign-funded firms face the highest energy price.

All three models are solved by linearization their first-order conditions.

4 Estimation

4.1 Indirect inference

This section provides an evaluation of the empirical relevance of a putty-clay investment or embodied technology in matching the regression coefficients estimated from the firm-level data.

To perform this evaluation, I construct a three-sector economy that nests both putty-clay and putty-putty investment model described in Section 3. I assume that in sector 1 output Y_t^{Putty} is produced using the putty-putty investment, sector 2 output $Y_t^{Clay-AK}$ is produced using the putty-clay investment without idiosyncratic productivity, and sector 3 output $Y_t^{Clay-CW}$ is produced using the putty-clay investment with idiosyncratic productivity described above. The total output in the economy is a combination of three sector outputs, $Y_t = (Y_t^{Putty})^{\theta_1}(Y_t^{Clay-AK})^{\theta_2}(Y_t^{Clay-CW})^{\theta_3}$, where $\theta_1+\theta_2+\theta_3 = 1$. In this setting, θ_i is the share of output produced using putty-putty or putty-clay investment, corresponding to the importance of disembodied technology (θ_1) and disembodied technology (θ_2 and θ_3).

The objective here is to recover this structural parameters $\theta = [\theta_1, \theta_2, \theta_3]'$. For any value of θ, I solve and simulate the three-sector model, then estimate equation (1) using the simulation data, and obtain a set of simulated coefficients $\beta^s = [\beta_1^s, \beta_2^s, \beta_3^s, \beta_4^s, \beta_5^s]^T$. Then θ is solved from the following minimization problem:

$$L(\theta) = \min_{\theta}[\beta^s(\theta) - \beta^d]W[\beta^s(\theta) - \beta^d]^T \tag{2}$$

where β^d is the coefficients from actual data, $\beta^s(\theta)$ is the coefficients from simulation data. W is the weighting matrix, identity matrix is used here. The equation (1) serves as the auxiliary model. θ is chosen in a way that two sets of estimated coefficients of the auxiliary model, using the actual data or simulation data, are as close as possible.

4.2 Estimation result

I apply the indirect inference estimation strategy to recover θ, for SOEs, non-SOEs and foreign-funded firms respectively. The estimated shares θ for three types of firms are reported in Table 4. For three types of firms, the shares of output produced by putty-clay investment are significantly greater than 0 and less than 1. Foreign-funded firms have a relatively smaller share of putty-clay technology, compared to their SOEs and domestic non-SOEs counterparts.

In order to see how this two-sector model reproduces the coefficients in equation (1), the coefficients from the simulation data β^s are reported in Table 5, in comparison with the coefficients from the actual data. For all three types of firms, the model with a combination of putty-clay and putty-putty successfully reproduces the contemporaneous impact of energy price on intensity, i.e., the coefficient β_1. However this model has some difficulty in reproducing the lagged impact, i.e., the coefficients $\beta_2, \ldots, \beta_5$.

5 Conclusion

This paper examines the role of embodied and disembodied technology change, and more specifically, measures quantitatively their contribution to achieving energy conservation. Specifically, we model the disembodied technology change as putty-putty investment, which assumes that capital are flexible and homogeneous. In contrast, we model the embodied technology change as putty-clay investment, which exhibits rigidity of energy intensity in new investment, and energy intensity of every vintage of capital is optimally chosen by firms. We incorporate both disembodied and embodied technology change, or by incorporating both putty-putty and putty-clay investment, into a DSGE model. Through indirect inference, the estimated DSGE model is able to reproduce the facts that observed directly from the firm-level data. This allows us to quantitatively measure the contribution of embodied technology change. The analysis concludes that 70-75% of energy conservation can be accounted for embodied technology change in Chinese industries from 1997 to 2004.

6 Tables

Table 1: Shares of Energy Sample in Aggregate Industry in 2004

Measure	All Industry		Of which: L&M Enterprises		Of which: Energy Sample	
Energy consumption (10,000 ton coal)	143,244	(100%)	na	na	81,117	(56.63%)
Sales Revenue (100 million yuan)	218,443	(100%)	126,284	(57.81%)	48,738	(22.31%)
Total Assets (100 million yuan)	240,707	(100%)	140,245	(58.26%)	63,129	(26.23%)
Employment (10,000 persons)	9,304	(100%)	3,232	(34.74%)	1,217	(13.08%)
No.of Enterprises	1,375,263	(100%)	23,267	(1.69%)	4,928	(0.36%)

Note: large and medium sized (L&M) eneterprises are industrial enterprises with annual sales over 30 million yuan, total assets over 40 million yuan and total employment over 300 persons. Numbers in parentheses are precentage of all industry.
Source: Statistical Yearbook of China 2005, NBS.

Table 3: Parameter values

Preference	β	γ	ϕ			
	0.997	1.5	3			
Production	λ	α	δ	σ	M	
	0.757	0.689	0.1	0.53	3	
Energy price	SOE		non-SOE		Foreign	
	μ	ρ	μ	ρ	μ	ρ
	0.581	0.392	0.654	0.412	0.726	0.400

Table 4: Estimation of Fractions θ

	SOE	NonSOE	Foreign
θ_1 (putty-putty)	0.24	0.25	0.29
θ_2 (putty-clay-AK)	0.10	0.10	0.10
θ_3 (putty-clay-CW)	0.66	0.65	0.61
$L(\theta)$	0.0198	0.0189	0.0273

Note: $L(\theta)$ is the value of the objective function defined in equation (2). The weighting matrix is identity matrix.

Table 2: Long-run Price Elasticity by Ownership Using Firm-level Energy Price (OLS)

	SOE				Non-SOE				Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Pe_t	-0.304***	-0.325***	-0.313***	-0.304***	-0.339***	-0.351***	-0.330***	-0.315***	-0.425***	-0.404***	-0.360***
	(0.010)	(0.013)	(0.018)	(0.025)	(0.014)	(0.020)	(0.027)	(0.035)	(0.027)	(0.035)	(0.046)
Pe_{t-1}	-0.206***	-0.147***	-0.159***	-0.126***	-0.217***	-0.121***	-0.119***	-0.074**	-0.221***	-0.135***	-0.126**
	(0.010)	(0.014)	(0.019)	(0.028)	(0.014)	(0.020)	(0.027)	(0.036)	(0.026)	(0.037)	(0.049)
Pe_{t-2}		-0.141***	-0.087***	-0.129***		-0.178***	-0.134***	-0.137***		-0.155***	-0.095**
		(0.012)	(0.017)	(0.025)		(0.017)	(0.025)	(0.032)		(0.030)	(0.042)
Pe_{t-3}			-0.111***	-0.066***			-0.163***	-0.141***			-0.179***
			(0.015)	(0.021)			(0.021)	(0.029)			(0.035)
Pe_{t-4}				-0.081***				-0.048*			
				(0.020)				(0.027)			
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11437	7327	4598	2831	8342	4891	3042	1803	2540	1530	954
R^2	0.713	0.734	0.751	0.755	0.700	0.718	0.734	0.750	0.788	0.819	0.851

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the dependent variable is log of energy intensity, Pe_t is log of energy price in year t, Pe_{t-1} is log of energy price in year t-1, and so forth. Longer lag price terms were added, but due to insiginificancy they are not reported in this table. The energy prices are firm-level prices.

Table 5: Comparison between Model and Data

	SOE		NonSOE		Foreign	
Coefficients	Model	Data	Model	Data	Model	Data
β_1	-0.2925***	-0.304***	-0.3017***	-0.315***	-0.3396***	-0.360***
		(0.025)		(0.035)		(0.046)
β_2	-0.0471***	-0.126***	-0.0508***	-0.074**	-0.0456**	-0.126**
		(0.028)		(0.036)		(0.049)
β_3	-0.0475***	-0.129***	-0.0507***	-0.137***	-0.0458**	-0.095**
		(0.025)		(0.032)		(0.042)
β_4	-0.0462***	-0.066***	-0.0490***	-0.141***	-0.0447	-0.179***
		(0.021)		(0.029)		(0.035)
β_5	-0.0008***	-0.081***	-0.0008	-0.048*		
		(0.020)		(0.027)		

Note: In the columns labeled "Model", the coefficients are estimated from the simulated data generated by the model that consists of three sectors. In the columns labeled "Data", the coefficients are regressed on the actual data. Standard errors in parentheses.