# The Role of Energy Efficient Technology and Vintage Capital in Chinese Industry

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**Abstract**

By incorporating energy-saving through both technology-embodied investment and embodied investment-specific technical change, as well as disembodied factor-neutral technical change into a dynamic stochastic general equilibrium (DSGE) model with heterogeneous investment, this paper deepens our understanding of the avenues through which firms adjust to rising energy prices. Using Chinese firm-level data from 1997-2004, we estimate a set of stylized facts regarding how firms of various ownership types respond to energy price changes. Through indirect inference, we then use these stylized facts to recover the key parameters in the DSGE model. The results show that within Chinese industry, in response to rising energy prices, state-owned enterprises, domestic non-state enterprises, and foreign-funded enterprises employ significantly different means to achieve their energy efficiency. Such differences can be substantially explained by government policy affecting energy pricing and the cost of investment finance across firms of different ownership types.

**Keywords**: energy price, putty-clay investment, vintage capital, embodied technology, disembodied technology, China

JEL classification: Q3, P2, E22

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# 1 Introduction

Many studies investigate the impact of changes in energy prices on energy production and energy consumption. As most simply estimate energy intensity-price elasticities, they suffer from a kind of "black box" effect meaning that when a firm or industry faces an exogenous increase in the price of energy, they employ unspecified channels to respond with varying degrees of energy conservation.

This paper seeks to construct a structural model, in the form of a dynamic stochastic general equilibrium (DSGE) model that includes a variety of pathways for energy-saving outcomes available to the firm. These include roles for energy-saving technologies, both disembodied and embodied in investment, to facilitate the achievement of energy conserving objectives.

A key feature of this model is the availability of two forms of technology-embodied investment, so-called "putty-clay" and "putty-putty" types of capital. While the former consists of vintages of capital with fixed energy-capital ratios, the latter, the putty-putty version, embodies a degree of flexibility, so that as energy prices change, the installed capital adapts to more optimal combinations of price-energy consumption. Notwithstanding the desirability of the flexible feature, because the flexible feature generally entails a cost premium – a higher initial price or ex post adjustment costs – firms may choose not to install the flexible putty-putty technology; rather they may choose the more rigid putty-clay technology. In our model, investment and technology – both neutral and factor-biased, endogenous and exogenous – jointly determine different factor efficiencies in the firms included in our study.

In recent years, with China having become the world's largest emitter of greenhouse gasses, attention has focused on China's industrial sector, including its evolving diversity across ownership types, and change in its industry mix. In this paper, we are able to employ a substantial panel of China's larger industrial firms to estimate energy price-intensity and energy price-investment relationships from which we identify salient stylized facts regarding the avenues through which firms of different ownership types – state-owned enterprises (SOEs), domestic non-state owned enterprises (NSOEs), and foreign-funded enterprises (FFEs) – respond to rising energy prices. Using these firm-level data, and recovering key structural parameters in the model, we are able to test the consistency of the model with the stylized facts that represent the various Chinese firm ownership types.

We investigate the proposition that firms choosing among the menu of technology-investment opportunities embedded in our model operate in different policy environments that make their choices different. Among these differences in policy environments are subsidies or guaranteed access to low-cost finance for state-owned enterprises, and the tendency of government to moderate market volatility and limit price changes, especially for SOEs, thus reducing the risk and cost of energy price fluctuations.

Due to a lack of detailed data on the vintage composition of the capital stock, existing empirical analyses of the relationship among energy prices, energy intensity, and investment are typically limited to a reduced-form regression analysis. Most firm- or industry-level data provide only the amount of capital stock or new investment over given periods. Although measures of the real capital stock or real investment are generally available, the quality of each vintage capital is not directly observable, making it challenging to construct quality-adjusted capital stock, or the vintage structure of capital, the exceptions being Gordon [1990] and Sakellaris and Wilson [2004]. Griffin and Schulman [2005] describe the challenge as follows:

*In a properly specified econometric demand model, the stocks of energy-using equipment would be modeled with of a number of investment and depreciation equations for each type of energy using capital. Energy consumption would then depend on the utilization and efficiency characteristics of the stock of equipment. Such an elaborate model could then be simulated to describe the adaption of the capital stock to energy price shock. But given the absence of capital stock data needed to reflect the adjustment of the capital stock of energy using equipment, econometricians estimate reduced form single demand equations featuring a distributed lag on price to capture the adaptation of the capital stock.*

This paper uses a novel approach to overcome the challenge caused by the absence of quality-adjusted vintage capital stock data. Given measures of each firm's net and gross capital stock valuations, both available in our data set, we construct a measure of the age structure of the capital stock as the ratio of net value to gross value of capital. Using this age structure measure, we then identify a robustly positive relationship between the age and energy efficiency across vintages. Given our proxy for the energy vintage structure and the stylized facts obtained from the reduced-form analysis, we are able to formulate and estimate our DSGE model for China's SOEs, domestic non-SOEs (NSOEs) and foreign funded firms (FFEs). The validity our model is demonstrated by its ability to replicate the stylized facts from firms of different ownership types.

Our results show that vintage capital that embodied energy efficiency technology plays a critical role in achieving energy efficiency for China's industrial firms. We find that the model with vintage capital, i.e., putty-clay investment, does a better job of replicating the dynamics between energy prices and energy intensity than do models without vintage capital investment. In comparison to domestic NSOEs and FFEs, SOEs rely more on investment-specific technology. SOEs tend to invest in capital goods that are more efficient when energy prices are high. Following SOEs, domestic NSOEs exhibit the next highest proportion of putty-clay investment, followed the FFEs that have the lowest proportion of putty-clay investment. Meanwhile, embodied capital or labor augmenting investment and disembodied factor-neutral technology are two additional channels through which firms reduces their energy intensity.

This paper is organized as follows. The next section presents a literature review with a focus on vintage capital models. Section 3 presents the empirical evidence that supports the existence of an active energy price-investment response in Chinese industry. Section 4 propose a DSGE model, which is able to explain the "stylized facts", or equivalently the regression results presented in Section 3. Within an inter-temporal optimizing framework, the DSGE model in Section 4 specifies the firm's investment choice in response to energy price changes. Section 5 identifies key structural parameters regarding the importance of vintage capital, embodied and disembodied technology, and shows the DSGE model successfully mimics the stylized facts in Section 3. Based on the DSGE model, Section 6 conducts a policy experiment to evaluate the effect of SOE reform on firm-level energy efficiency. Conclusions are drawn in Section 7.

# 2 Literature Review

This paper builds directly on the work of Wei [2003] and Gilchrist and Williams [2000], who develop a modern business cycle version of the putty-clay theory of Johansen [1959]. Gilchrist and Williams [2000] first propose a putty-clay model and empirically estimate of the relative importance of putty-clay investment in the U.S. economy. With two factors in their model – capital and labor - the authors focus on how the aggregate economy responds to exogenous productivity shocks, such as investment-specific technology shocks and total factor productivity shocks. Their model does not include energy price shocks. However, Wei [2003] extends the work of Gilchrist and Williams [2000] to include energy, thereby enabling the analysis of how a firm's market value responds to exogenous energy price shocks. Wei [2003] examines the implications of putty-clay investment for the stock market crash during the 1973 oil crisis. However, Wei [2003]'s study does not assess the relative importance of putty-clay and putty-putty investment.

Much of the research that follows from Gilchrist and Williams [2000] and Wei [2003] focuses on the impact of energy price shocks on the aggregate economy or on financial markets, e.g., Kilian [2008], Kilian and Park [2009], Gourio [2011], Balcilar et al. [2015], Mohaddes and Pesaran [2017], and Sim and Zhou [2015].

Atkeson and Kehoe [1999] is the first paper to use putty-clay investment to study the relationship between energy prices and energy use. Based on Atkeson and Kehoe [1999], Díaz and Puch [2019] and Rausch and Schwerin [2016] propose dynamic models with putty-clay investment and investment-specific technology to study the features of the balanced growth path. Empirically, Díaz and Puch [2019] and Rausch and Schwerin [2016] use their putty-clay investment model to study the relationship among energy prices, energy use, the capital-energy ratio, and other factors on the balanced growth path, based on US aggregate economy. Our paper differs from these two papers in the two respects. First, in Díaz and Puch [2019] and in Rausch and Schwerin [2016], vintages of capital can only combine with fixed amounts of energy, thereby requiring a fixed capital-energy ratio. However, by allowing substitution between labor and capital services, all vintage capital becomes fully utilized if energy prices are low enough. In our model, as in Wei [2003] and Gilchrist and Williams [2000], there is no substitutability among capital, energy and labor, the utilization decision of a particular vintage of capital is therefore endogenously determined in the model. Second, the focus of these other papers, however, is not the empirical relevance of putty-clay investment versus putty-putty investment. This paper quantifies the relative importance of the two modes of investment across different firm ownership types for the purpose of achieving energy efficiency in China's industry firms.

A second well-establish body of literature is the analysis on China's energy intensity. This body of research can be classified roughly into two groups according to the methods applied: the first group uses decomposition methods; the second group uses regression methods. As noted in the Introduction, most researchers and experts in this area concentrate their research on deriving energy-intensity price elasticities.Many of these studies are well-known among scholars, who focus on energy conservation in Chinese industry. Table A1 in the Appendix A lists a number of relevant paper studying China's energy intensity.

A third related stream of literature relates to the impact of energy prices on investment. Pindyck and Rotemberg [1983] use a dynamic factor input model to estimate the demand of capital in response to energy price changes, using US annual data from1948 to 1971. Edelstein and Kilian [2007] investigate the impact of energy prices on the fixed assets of U.S. firms. Ratti et al. [2011] estimate the impact of energy prices on the investment decisions of European firms. Sadath and Acharya [2015] study how investment in Indian manufacturing firms responds to energy prices. Wang et al. [2018] empirically analyze the effect of international oil price volatility on China's corporate investment. And Phan et al. [2019] show that crude oil price uncertainty negatively influences corporate investment from 54 countries in 1984-2015. All these regression analysis show the negative impact of volatility in energy prices on firm or industry investment.

However, the price-investment channel – firms investing in energy-efficient capital when energy price rises – has not been explored fully. One relevant paper is Gamtessa and Olani [2018], who apply a panel VAR to estimate the effect of energy price shocks on energy intensity, using Canadian industry-level data from 1961-2007. Their regression analysis supports the proposition that in response to an increase in energy prices, industrial firms employ more already-installed energy-saving capital in the short run, while also investing in new energy-saving capital in the long run. Other studies (Parker and Liddle [2016], and Wu [2012]) investigate the investment channel by adding variables that serve as proxies for capital's vintage structure, such as new investment or the growth rates of the capital stock, into energy intensity regressions.

Summarizing, this paper draws most directly on Gilchrist and Williams [2000] and Wei [2003]. Considering the existing literature, the value added of this study consists of devising and estimating a structural model in which for given energy prices, the firm chooses optimal combination of energy-saving vintages of investment in a setting that includes a variety of channels of factor-augmenting embodied and disembodied technical change. Furthermore, our paper applies this vintage capital model with multiple avenues for adapting to changing energy prices to three principle ownership types in Chinese industry, likely the most important single source of global warming and carbon emission in today's world.

# 3 Stylized Facts

This section presents the "stylized facts" using the firm-level data in Chinese industries from 1997-2004. These facts are framed to examine the core structural parameters in the model we develop to study the roles of energy-efficient technology and the vintage composition of energy-conserving investment.

We use three sets of regressions to characterize the relationships among energy price, energy intensity (the ratio of energy consumption $En$ over output $Y$) and new investment. For readers' convenience and sake of completeness, we only re-present the three sets of regressions in this section. The detailed description of the data set and variable constructions can be found in Tang [2020].

First, we employ the standard energy intensity regression equation to summarize the relationship between energy intensity ($En/Y$) and energy price ($P^e$) as follows:

$$\ln(\frac{En}{Y})_{i,t} = \beta_0 + \beta_1 \ln P^e_{i,t} + \beta_2 \ln P^e_{i,t-1} + \beta_3 \ln P^e_{i,t-2} + \beta_4 \ln P^e_{i,t-3} + \beta_5 \ln P^e_{i,t-4} + \text{controls}_{i,t} + \xi_{i,t} \quad (1)$$

where the dependent variable is the logarithm of energy intensity of firm $i$ in year $t$; the explanatory variables are the logarithmic values of real energy prices in the current year (denoted as $P^e_{i,t}$) and in past years (denoted as $P^e_{i,t-j}$). The lagged energy price terms capture the dynamic effect of energy prices on energy intensity. The control variables include year dummies and dummies for the two-digit industrial classification and provincial setting for each firm. Equation (1), which captures the impact of energy prices on energy intensity, hereafter is referred to as Regression 1.

Equation (1) is estimated using OLS for three sub samples: state-owned enterprises (SOEs), domestic non-state-owned enterprises (NSOEs), and foreign-funded enterprises (FFEs) separately. The regression results are presented in Table 1. The upper panel A of Table 1 corresponds to the estimation results for SOEs, the middle panel B corresponds to NSOEs, and the lower panel C is for FFEs. Longer lagged price terms beyond $t-4$ were added; however, they are not reported due to their coefficients having been statistically insignificant.

Table 1: Regressing energy intensity on energy prices by ownership (OLS)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Panel A: SOEs | | | | | |
| $P^e_t$ | $-0.389^{***}$ | $-0.304^{***}$ | $-0.325^{***}$ | $-0.313^{***}$ | $-0.304^{***}$ |
| | (0.010) | (0.014) | (0.017) | (0.024) | (0.036) |
| $P^e_{t-1}$ | | $-0.206^{***}$ | $-0.147^{***}$ | $-0.159^{***}$ | $-0.126^{***}$ |
| | | (0.013) | (0.017) | (0.023) | (0.033) |
| $P^e_{t-2}$ | | | $-0.141^{***}$ | $-0.087^{***}$ | $-0.129^{***}$ |
| | | | (0.016) | (0.021) | (0.026) |
| $P^e_{t-3}$ | | | | $-0.111^{***}$ | $-0.066^{***}$ |
| | | | | (0.019) | (0.024) |
| $P^e_{t-4}$ | | | | | $-0.081^{***}$ |
| | | | | | (0.023) |
| Panel B: NSOEs | | | | | |
| $P^e_t$ | $-0.441^{***}$ | $-0.339^{***}$ | $-0.351^{***}$ | $-0.330^{***}$ | $-0.315^{***}$ |
| | (0.012) | (0.017) | (0.025) | (0.037) | (0.047) |
| $P^e_{t-1}$ | | $-0.217^{***}$ | $-0.121^{***}$ | $-0.119^{***}$ | $-0.074^{**}$ |
| | | (0.015) | (0.020) | (0.030) | (0.036) |
| $P^e_{t-2}$ | | | $-0.178^{***}$ | $-0.134^{***}$ | $-0.137^{***}$ |
| | | | (0.018) | (0.023) | (0.031) |
| $P^e_{t-3}$ | | | | $-0.163^{***}$ | $-0.141^{***}$ |
| | | | | (0.021) | (0.028) |
| $P^e_{t-4}$ | | | | | $-0.048^{*}$ |
| | | | | | (0.026) |
| Panel C: FFEs | | | | | |
| $P^e_t$ | $-0.525^{***}$ | $-0.425^{***}$ | $-0.404^{***}$ | $-0.360^{***}$ | $-0.467^{***}$ |
| | (0.020) | (0.031) | (0.040) | (0.057) | (0.090) |
| $P^e_{t-1}$ | | $-0.221^{***}$ | $-0.135^{***}$ | $-0.126^{**}$ | 0.002 |
| | | (0.028) | (0.043) | (0.063) | (0.112) |
| $P^e_{t-2}$ | | | $-0.155^{***}$ | $-0.095^{**}$ | $-0.075$ |
| | | | (0.032) | (0.043) | (0.057) |
| $P^e_{t-3}$ | | | | $-0.179^{***}$ | $-0.134^{**}$ |
| | | | | (0.038) | (0.054) |
| $P^e_{t-4}$ | | | | | $-0.089^{*}$ |
| | | | | | (0.052) |

Robust Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: the dependent variable is log of energy intensity, $P^e_t$ is log of energy price in year t, $P^e_{t-1}$ is log of energy price in year $t-1$, etc. All regressions include year, 2-digit industry and province dummies. To save space, $R^2$ and number of observations are not reported here.

For all SOEs, NSOEs and FFEs, the regression coefficients of current and lagged energy prices are significantly negative, and the contemporaneous impact of energy prices on energy intensity is larger than that of lagged energy prices. In all the regressions, the coefficients for the current energy price are significantly different from -1, which implies that energy intensity is inelastic to changes in current energy prices. The inelastic or sluggish reaction of energy intensity to current energy prices is consistent with findings in Lin and Xu [2019], who use province-level data in the metallurgical industry from 2003 to 2015, and Fisher-Vanden et al. [2016], who also use firm-level data to investigate energy intensity in four energy-intensive industries in China.

This pattern of regression coefficients – magnitudes of coefficients of current energy prices that are less than unity and non-zero coefficients of lagged energy prices – contradicts predictions associated with Cobb-Douglas production function, which is widely used in empirical analysis. Under the assumption of the Cobb-Douglas production function, the coefficients for current energy prices should always be -1, consistent with the unitary elasticity of substitution among factor inputs. And the coefficients of all lagged energy prices are expected to be 0, because current energy intensity only depends on current energy price. That is to say, there should be no vintage effect in a Cobb-Douglas production function or in a putty-putty investment setting. That the pattern of coefficients from Regression 1 clearly contradict from predictions associated with Cobb-Douglas production function motivates us to introduce the putty-clay investment or vintage capital into the DSGE model in Section 4.

Next we investigate the role of the vintage capital channel through which firms can decrease their energy intensities in the long run. One hypothesis is that for firms that depend on technology-embodied investment, when energy prices rise, firms are incentivized to invest in energy-efficient capital goods, which in turn reduces energy intensity. To test this hypothesis, we apply the following two regressions:

$$\ln(\frac{En}{Y})_{i,t} = \alpha_0 + \alpha_1 \ln P^e_{i,t} + \alpha_2 \ln(\frac{NVFA}{OVFA})_{i,t} + \alpha_3 \frac{1}{s}\sum_{j=1}^{s} \ln P^e_{i,t-j} + \text{controls}_{i,t} + \varepsilon_{i,t} \tag{2}$$

$$\ln(\frac{NVFA}{OVFA})_{i,t} = \gamma_0 + \gamma_1 \frac{1}{s}\sum_{j=0}^{s} \ln P^e_{i,t-j} + \text{controls}_{i,t} + \upsilon_{i,t} \tag{3}$$

In Equation (2), we add one key explanatory variable, the log of $NVFA/OVFA$, a proxy for the vintage structure of the capital stock, which becomes the dependent variable in Equation (3).

We use the net value of fixed assets, $NVFA$, and the original value of fixed assets, $OVFA$, to construct a ratio, $NVFA/OVFA$, as proxy for the vintage structure of a firm's capital stock. The older the capital, the greater degree of depreciation, causing this ratio to diminish. This ratio $NVFA/OVFA$ lies in the range of 0 and 1. At one extreme, all vintages of capital that materialize through investment in current period have a value of $NVFA/OVFA = 1$. At another extreme, if all capital had materialized long time ago, then the ratio $NVFA/OVFA$ would converge toward 0. Thus, the younger a firm's capital structure, the higher the ratio $NVFA/OVFA$.

Within the existing literature that investigates the price-investment channel, Gamtessa and Olani [2018], Parker and Liddle [2016] and Wu [2012] add new investment or the growth rate of the capital stock as an explanatory variable in energy efficiency regressions to estimate the effect of capital on energy efficiency. Nevertheless, investment in one period is not enough to capture the age structure of capital stock. Given the shortcomings of these measures, we use the $NVFA/OVFA$ ratio to measure the age/vintage structure of the capital stock.

Equation (2), hereafter referred to as Regression 2, identifies the contribution of the capital's age structure to changes in energy intensity. As such, it determines the extent to which the age structure is a suitable proxy as a vintage measure of capital. Equation (3), which we reference as Regression 3, tests the responsiveness of our age/vintage capital measure to energy price changes.

To maintain the parsimony of the regression Equation (2) and (3), we use moving averages of past energy prices as a regressor to capture the impact of lagging energy prices on energy intensity. The control variables include year dummies and dummies for the two-digit industrial classification and provincial setting for each firm.

Table 2 reports the estimation results of Equation (2), which shows how capital's vintage structure affects the energy intensity for the three sub-samples individually: SOEs, NSOEs and FFEs. The coefficients on current and lagged energy prices are significantly negative in all the regressions. Moreover, the coefficients of $NVFA/OVFA$ suggest that only SOEs and NSOEs use newer vintages of investment as a means for reducing their energy intensity, while FFEs do not reduce energy intensity through new investment. The negative coefficient for $NVFA/OVFA$ indicates that firms with higher ratios of NVFA to OVFA tend to be more energy efficient. This suggests the SOEs and/or NSOEs reduce their energy intensity by investing in new capital that is relatively more energy efficient.

Table 2: Energy intensity responding to the vintage structure NVFA/OVFA by ownership (OLS)

| | (1) | (2) 1-year | (3) 2-year | (4) 3-year | (5) 4-year |
|---|---|---|---|---|---|
| Panel A: SOEs | | | | | |
| $P^e_t$ | $-0.387^{***}$ | $-0.303^{***}$ | $-0.323^{***}$ | $-0.324^{***}$ | $-0.318^{***}$ |
| | (0.010) | (0.014) | (0.017) | (0.023) | (0.032) |
| $\frac{NVFA}{OVFA}$ | $-0.125^{***}$ | $-0.108^{***}$ | $-0.148^{***}$ | $-0.128^{***}$ | $-0.132^{***}$ |
| | (0.039) | (0.050) | (0.034) | (0.038) | (0.050) |
| Lagged $P^e$ | | $-0.205^{***}$ | $-0.285^{***}$ | $-0.339^{***}$ | $-0.379^{***}$ |
| | | (0.013) | (0.018) | (0.025) | (0.035) |
| Panel B: NSOEs | | | | | |
| $P^e_t$ | $-0.440^{***}$ | $-0.337^{***}$ | $-0.341^{***}$ | $-0.320^{***}$ | $-0.309^{***}$ |
| | (0.012) | (0.017) | (0.024) | (0.034) | (0.043) |
| $\frac{NVFA}{OVFA}$ | $-0.106^{***}$ | $-0.160^{***}$ | $-0.180^{***}$ | $-0.227^{***}$ | $-0.215^{***}$ |
| | (0.023) | (0.032) | (0.050) | (0.048) | (0.063) |
| Lagged $P^e$ | | $-0.217^{***}$ | $-0.305^{***}$ | $-0.422^{***}$ | $-0.408^{***}$ |
| | | (0.015) | (0.024) | (0.036) | (0.048) |
| Panel C: FFEs | | | | | |
| $P^e_t$ | $-0.525^{***}$ | $-0.425^{***}$ | $-0.401^{***}$ | $-0.349^{***}$ | $-0.415^{***}$ |
| | (0.020) | (0.031) | (0.038) | (0.048) | (0.066) |
| $\frac{NVFA}{OVFA}$ | 0.053 | 0.012 | 0.013 | 0.018 | 0.051 |
| | (0.038) | (0.042) | (0.049) | (0.056) | (0.091) |
| Lagged $P^e$ | | $-0.222^{***}$ | $-0.292^{***}$ | $-0.403^{***}$ | $-0.343^{***}$ |
| | | (0.028) | (0.040) | (0.050) | (0.071) |

Robust Standard errors in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Note: the dependent variable is log energy intensity, $P^e$ is log of the current energy price, $NVFA/OVFA$ represents current vintage structure in capital, and Lagged $P^e$ is the moving average of lagged log energy price. In the column (1), no lagged energy price is included; in the column (2) labeled with "1-year", the Lagged $P^e$ is $P^e_{t-1}$, the 1-year lagged energy price; in the column (3) labeled with "2-year", the Lagged $P^e$ is $\frac{1}{2}(P^e_{t-1} + P^e_{t-2})$, the moving average energy price in $t-1$ and $t-2$, and so forth for the rest of columns. All regressions include year, 2-digit industry and province dummies. To save space, $R^2$ and number of observations are not reported here.

Table 3 reports the regression results of Equation (3), which shows how vintage structure responds to current and lagged energy prices, for SOEs, NSOEs and FFEs, separately. For SOEs, the positive coefficient for $NVFA/OVFA$ suggests that rising energy prices encourage SOEs to undertake more new investment. For NSOEs, new investment responds to the current energy price, but the coefficients of past energy prices are no longer significant. The Table 3 results show that the investment of FFEs appears to be indifferent to price changes.

Table 3: Vintage structure NVFA/OVFA response to lagged energy price by ownership (OLS)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | 1-year | 2-year | 3-year | 4-year |
| Panel A: SOEs | | | | | |
| Lagged $P^e$ | 0.012*** | 0.013*** | 0.031*** | 0.040*** | 0.059*** |
| | (0.003) | (0.005) | (0.005) | (0.007) | (0.009) |
| Panel B: NSOEs | | | | | |
| Lagged $P^e$ | 0.010*** | 0.009 | 0.010 | 0.007 | 0.004 |
| | (0.004) | (0.005) | (0.007) | (0.009) | (0.011) |
| Panel C: FFEs | | | | | |
| Lagged $P^e$ | 0.003 | 0.003 | −0.012 | −0.015 | 0.006 |
| | (0.007) | (0.011) | (0.014) | (0.022) | (0.027) |

Robust Standard errors in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Note: the dependent variable is the log of $NVFA/OVFA$, and Lagged $P^e$ is the moving average of lagged log energy price. In the column (1), Lagged $P^e$ is energy price in current year. In the column (2) labeled with "1-year", Lagged $P^e$ corresponds $\frac{1}{2}(P_t^e + P_{t-1}^e)$. And in the column (3) labeled with "2-year Lagged $P^e$ is $\frac{1}{3}(P_t^e + P_{t-1}^e + P_{t-2}^e)$, and so forth for the rest of columns. All regressions include year, 2-digit industry and province dummies. To save space, $R^2$ and number of observations are not reported here.

The different investment responses from SOEs relative to NSOEs and FFEs could be explained by preferential government treatment for SOEs. Central or local governments may provide subsidies or other support to SOEs, thereby enabling SOEs to sustain their investment even when energy prices are rising. One motivation for sustained SOE investment is the fact that local government officials in China are rewarded and promoted based on local economic development, as measured mainly by GDP growth. In support of this proposition, Brandt and Li [2003], Bailey et al. [2011] and Song et al. [2011] present evidence that banks in China prefer to give loans to SOEs and discriminate against firms of other ownership types. Hence, when energy prices increase, SOEs might not be as financially constrained as other types of firms. Consistent with this proposition, Regression 2 and Regression 3 together show that, in the long run, rising energy prices induce firms to invest in energy efficient capital, especially for SOEs.

The second interpretation of the relative absence of investment responsiveness to energy prices among NSOEs and FFEs firms is the greater likelihood that they have invested in relatively flexible types of capital stock. That is NSOEs and FFEs firms may have invested in putty-putty vintages of capital stock. By contrast, perhaps due to available investment subsidies and/or due to relatively stable energy prices, resulting from government energy price controls, SOEs have tended to be less forward-looking in their investment activity. The average energy prices for SOEs, NSOEs and FFEs are: 0.388, 0.409, and 0.631, respectively, while the standard deviations of these prices are 0.584, 0.672, and 0.943, respectively. Because the mean and standard deviation of energy prices for SOEs are somewhat less than those for counterpart NSOEs, while substantially less than those for FFEs, SOEs tend to be less forward-looking in their investment activity.

More robustness check can be found in Tang [2020], the regression results share similar patterns as reported here. Hence, for the purpose of its baseline reference, the model we propose in Section 4 aims to replicate the stylized facts as shown in Tables 1, 2 and 3.

We do not assert that the regression coefficients in Regressions 1, 2 and 3 are consistent, such as coefficients in Regression 1 are price-elasticities, and these 3 sets regressions are the correct specification. We interpret these regression coefficients as correlation coefficients, which summarize the relationships among energy price, energy intensity and new investment. Regressions 1, 2, and 3 are auxiliary regressions, whose purpose is to help us recover structural parameters in the DSGE model in Section 4. In Section 5, we apply the exact same specifications of Equations (1), (2) and (3) to a synthetic data generated by the model.

# 4 The Model

In this section, we formulate key components in the DSGE model, with salient features adopted from Gilchrist and Williams [2000] and Wei [2003]. The detailed specification and derivation of the full model can be found in Gilchrist and Williams [2000] and Wei [2003]. [1]

On the production side, there are two sectors: putty-clay sector and putty-putty sector. Firms in both sectors use capital ($K$), energy ($En$), and labor ($L$), to produce output ($Y$). Energy and labor are homogeneous and can be reallocated across firms and sectors with no cost. Capital is heterogeneous. Each vintage capital depreciates at a rate $\delta$ in a period and is fully scrapped after $M$ periods.

In the putty-putty sector, each vintage of capital is characterized by its vintage and investment-specific technology. The firm's production technology is described by a vintage Cobb-Douglas production function. Following the terminology from Gilchrist and Williams [2000] and Wei [2003], the vintage capital is referred as "machines". Specifically, the output produced by machine $i$ with vintage $t-j$ in period $t$ is:

$$Y^P_{i,t-j,t} = A_t \cdot \theta_{i,t-j} \cdot K^{\lambda\alpha}_{t-j,t} \cdot En^{(1-\lambda)\alpha}_{t-j,t} \cdot L^{1-\alpha}_{t-j,t} \tag{4}$$

where $A_t$ represents economy-wide disembodied factor-neutral technological change, and $\theta_{i,t-j}$ is machine-level idiosyncratic efficiency, which remains fixed for the $M$-period lifespan of each vintage. We assume that

[1]The detailed specification of the model, its first-order conditions and solution programs are available from authors upon request.

$\theta_{i,t-j}$ is a log-normally distributed random variable. Namely,

$$\ln \theta_{i,t-j} \sim N(\ln \theta_{t-j} - \frac{1}{2}\sigma^2, \sigma^2) \tag{5}$$

where $\sigma^2$ is the variance of the idiosyncratic shock, and the aggregate index $\theta_{t-j}$ represents investment-specific technology, or capital-augmented technology of vintage $t-j$ . This embodied investment-specific technology $\theta_{t-j}$only affects production efficiency of vintage $t-j$, and remains unchanged for $M$ periods after installation. On the contrary, the disembodied technology $A_t$ affects the production efficiency for all vintages in period $t$.

The investment-specific technology, $\theta_t$, first introduced by Greenwood et al. [1997], refers to technology advances that make capital goods more productive, efficient, and less expensive. In our model, we assume that investment-specific technology $\theta_t$ follows the process as:

$$\ln \theta_t = \rho_\theta \ln \theta_{t-1} + \rho_{p\theta}(\ln P^e_{t-1} - \ln \bar{P}) + v_t \tag{6}$$

where $v_t \sim iidN(0, \sigma^2_\theta)$.

In addition to the investment-specific technology, we assume economy-wide factor-neutral disembodied technology $A_t$ follow the process as:

$$\ln A_t = \rho_A \ln A_{t-1} + \rho_{pA}(\ln P^e_{t-1} - ln\bar{P}) + \varsigma_t \tag{7}$$

where $\varsigma_t \sim iidN(0, \sigma^2_A)$.

Different from existing literature, (for instance in Gilchrist and Williams [2000], Wei [2003], Díaz and Puch [2019] and Rausch and Schwerin [2016]), we add two key parameters, $\rho_{p\theta}$ and $\rho_{pA}$, to model the energy-price induced innovation. That $\rho_{p\theta} > 0$ indicates that firms tend to use more efficient investment or capital goods with a higher $\theta_t$ when energy prices rise. Likewise, a positive $\rho_{pA}$ implies that firms tend to adopt a better disembodied technology in response to higher energy prices. This is in accordance with Popp [2001] and Popp [2002], who provide evidence on the energy-price induced technology advance in U.S.

By imposing the restriction of no ex-post substitution among factor inputs, we obtain the production function for putty-clay investment. As stated in Equation (4), once a machine is installed, its capital-energy ratio, $K/En$, and energy-labor ratio, $En/L$, are fixed for the following $M$ periods. Hence, the output produced by machine $i$ with vintage $t-j$ in period $t$ in putty-clay sector is:

$$Y^C_{i,t-j,t} = A_t \cdot \theta_{i,t-j} \cdot k^{\lambda\alpha}_{k-j} \cdot e^{\alpha}_{t-j} \cdot L_{i,t-j,t} \tag{8}$$

where $k_{t-j}$ and $e_{t-j}$ are the fixed capital-energy ratio $K/En$, and fixed energy-labor ratios $En/L$ of machines with vintage $t-j$, and $L_{i,t-j,t}$ is the amount of labor used to these machines, which is normalized to be unity under the constant-returns-to-scale assumption. Hence, in the putty-clay sector, capital goods are heterogeneous in terms of its vintage $t-j$, capital-energy ratio $k_{k-j}$ and energy-labor ratio $e_{t-j}$ chosen at the time of installation, and the value of idiosyncratic efficiency term $\theta_{i,t-j}$.

In the putty-putty sector, firms only chooses the profit-maximizing amount of investment; in the putty-clay sector, firms not only choose the amount of investment (the extensive margin), but also the capital-energy ratio $k$ and energy-labor ratio $e$ (the intensive margin). The capital-energy ratio and energy-labor ratio chosen by firms are the energy-efficient technology embodied in new investment. These elements are absent in the putty-putty sector. In summary, firms employ various channels to achieve energy efficiency. These channels are: disembodied factor-neutral technology $A_t$, embodied investment-specific technology $\theta_t$ and energy-efficient technology embodied in vintage capital, such as the choice of capital-energy ratio in investment.

Firms in both sectors respond to exogenous energy prices, which are assumed to follow an AR(1) process:

$$\ln P^e_{t+1} - \ln \bar{P} = \rho_P (\ln P^e_t - ln\bar{P}) + \varepsilon_{t+1} \tag{9}$$

where $\varepsilon_{t+1} \sim iidN(0, \sigma^2_p)$, $\bar{P}$ is the unconditional mean of the energy price, normalized to be one, and $\rho_p$ is the persistence parameter of the energy price process.[2]

In each sector, firms choose the profit maximizing quantities of labor, energy and investment; the total output produced in each sector is the aggregation of output over all machines and all vintages is $Y^p_t = \sum_{j=1}^{M} \int_{\theta_{i,t-j}} Y^P_{i,t-j,t} \cdot f(\theta_{i,t-j}) \cdot d\theta_{i,t-j}$, and $Y^C_t = \sum_{j=1}^{M} \int_{\theta_{i,t-j}} Y^C_{i,t-j,t} \cdot f(\theta_{i,t-j}) \cdot d\theta_{i,t-j}$, where $f(\theta_{i,t-j})$ is density function of the log-normal variable in Equation (5).

In a two-sector economy in which both putty-putty and putty-clay technologies operate, final-goods output

[2] Fisher-Vanden et al. [2016] and Tang [2020] argue that the firm-level energy prices are exogenous to a large degree, based on the energy price setting institution in China. Here the assumption that energy prices are exogenous is of course a simplification. The focus of our research is to have a model, which is able to replicate the stylized facts in the data. Section 5 does demonstrate that this model with exogenous energy prices is able to mimic salient features observed in the firm-level data.

produced by output from the putty-putty sector ($Y_t^p$) and output from putty-clay sector ($Y_t^c$) is:

$$Y_t = (Y_t^p)^{1-\eta}(Y_t^c)^{\eta} \tag{10}$$

One key structural parameter we intend to recover is $\eta$, the share of output produced by the putty-clay sector. If the estimated value of $\eta$ is close to unity, the data effectively places a large weight on putty-clay production in order to match the regression coefficients obtained in Section 3. On the other hand, if the estimated value of $\eta$ is close to zero, the data suggest little, if any, role for putty-clay capital for the purpose of matching the regression coefficients in Section 3.

# 5 Estimating the model parameters

In this section, we first introduce indirect inference estimation, then discuss the identification strategy that allows us to recover the structural parameters from the model through the regression coefficients, which are directly observable from actual data. Thereafter, the estimations of structural parameters are presented and discussed.

## 5.1 Indirect inference estimation

There are two sets of parameters in the model. The structural parameters, such as the share of putty-clay investment, and the process of disembodied and embodied technology, are estimated via indirect inference. Another set of parameters in utility and production function are calibrated.[3] The calibrated parameters values are presented in Table 11 in Appendix B.

Because the model described in Section 4 has no analytical closed-form solution, consequently we are not able to find the functional form of energy intensity, the dependent variables in Equation (1) and (2), and $NVFA/OVFA$, the dependent variable in Equation (3). Hence, the structural parameters can not be estimated using standard regression techniques. Instead,we use the indirect inference estimation routine, which minimizes the distance between the model's moments and the counterpart data moments.

In general, for a given vector $\psi$ of unknown model parameters, we first solve the model. The resulting decision rules are then used to simulate a synthetic data set. Next we run the three sets of regressions, described in Equations (1)- (3) on this synthetic data set, and the regression coefficients, $g_M(\psi)$, are obtained.

[3] In principle, every parameter in the model can be estimated, but in practice the size of the estimated parameter space is limited by computational constraints. Therefore, in this research we estimate the parameters about which there are probably the weakest prior.

Last, we compare the regression coefficients based on the synthetic data, with the regression coefficients obtained directly from the actual data. At the end, the estimated structural parameters $\hat{\psi}$ are obtained by solving the following minimization problem:

$$J(\psi) = \min_{\psi}[g_M(\psi) - g_d]^T W[g_M(\psi) - g_d] \tag{11}$$

where $g_d$ is a vector of regression coefficients using actual data, $g_M(\psi)$ is a vector of regression coefficients using simulated data generated by the model, and $W$ is the optimal weighting matrix. $J(\psi)$, the value of the objective function in Equation (11), provides a chi-square test for the equality between $g_M(\psi)$ and $g_d$. The detailed descriptions of model solution and computational strategy are present in Appendix B.

Specifically, the vector of structural parameters to be estimated is:

$$\psi = \{\eta, \rho_P, \rho_\theta, \rho_{p\theta}, \rho_A, \rho_{pA}, \frac{\sigma_\theta}{\sigma_p + \sigma_\theta + \sigma_A}, \frac{\sigma_A}{\sigma_p + \sigma_\theta + \sigma_A}\}.[4]$$

And $g_d$ are the 34 coefficients from three sets of regressions, which are reported in Tables 1-3. [5]

The regression coefficients in Equations (1)-(3) are selected because they are informative about the underlying parameters. Theoretically, the regression coefficients based on the model $g_M$ are some nonlinear intractable functions of structural parameters $\psi$. [6] Hence we are able to recover the unobservable structural parameters through observable regression coefficients.

Intuitively, $\eta$, the proportion of putty-clay investment, and $\rho_P$, the auto-correlation of energy prices, can be identified from coefficients in Regression 1. At one extreme, if $\eta$ equals to 0, then the production function is essentially Cobb-Douglas, indicating that the coefficient for the current energy price being -1, and the coefficients of all lagged energy prices being 0 in Regression 1. At the other extreme, if $\eta = 1$, then the production function is of the Leontief form, in which the factor input ratios are fixed. This condition would imply: first the coefficient for the current energy price in Regression 1 is close to 0, this is because firms can hardly change the current energy consumption due to the fixed input ratios. Second, the coefficients of all lagged energy prices would be negative, this is because firms would invest in energy-efficient capital if energy prices rose in the past, so its vintage structure depends on past energy prices. Hence, past energy prices influence current energy intensity through capital's vintage structure.

[4] Because we solve this model by linearizing all the first-order conditions, the regression coefficients based on the model only depend on the relative magnitude of standard deviations of 3 structural shocks, i.e., $\sigma_\theta/\sigma_p$, $\sigma_A/\sigma_p$, not absolute values of $\sigma_p$, $\sigma_\theta$, $\sigma_A$. Although the absolute values of $\sigma_p$, $\sigma_\theta$, $\sigma_A$ can be estimated by matching the standard errors of 34 regression coefficients, adding more structural parameters in indirect inference estimation routine would increase computational time exponentially. Thus, in this paper, we estimate the relative magnitudes of 3 structural shocks' standard deviations.

[5] There are 15 regression coefficients in Table 1, 14 coefficients in Table 2 and 5 coefficients in Table 3.

[6] The detailed discussion on the mapping of $\psi$ to $g_M$ is in Appendix B.

The parameters, $\{\rho_\theta, \rho_{p\theta}, \rho_A, \rho_{pA}, \sigma_\theta/(\sigma_p + \sigma_\theta + \sigma_A), , \sigma_A/(\sigma_p + \sigma_\theta + \sigma_A)\}$, that govern the processes of investment-specific technology $\theta_t$ and disembodied technology $A_t$, can be identified mainly from coefficients in Regression 2 and Regression 3. Without this embodied and disembodied technology, firms will lower investment when energy prices rise. When energy prices rise, the firm's profit will decrease, so that investment will decrease; also, when energy prices rise, capital goods become less efficient, causing the marginal benefit of investment to decrease, so firms will choose to invest less in the future. Both income effect and substitution effect dictate firms to reduce investment; therefore, our measure of capital's vintage age-structure $NVFA/OVFA$ will decrease. This indicates the coefficients of $NVFA/OVFA$ in Regression 2 are expected to be positive, and the coefficients of energy prices in Regression 3 are expected to be negative. In order to reproduce the coefficients in Regression 2 and 3, adding $\theta_t$ and $A_t$ will increase the marginal benefit of investment or increase profit in the future, mitigating the substitution and income effects, hence enabling the model to generate coefficients in Regressions 2 and 3 similar to those based on data. The standard deviation of innovation in embodied and disembodied technologies also affect the firm's investment decision, as firms tend to wait and reduce investment if the second moment of innovation or uncertainty increases, see in Dixit et al. [1994]. Several empirical analysis, see in Wang et al. [2018] and Phan et al. [2019], also find that energy price uncertainty negatively influence firm's investment, using firm-level data.

In sum, the 34 coefficients from the three sets of regressions reported in Tables 1-3 are jointly determined by the eight structural parameters, $\psi = \{\eta, \rho_P, \rho_\theta, \rho_{p\theta}, \rho_A, \rho_{pA}, \sigma_\theta/(\sigma_p + \sigma_\theta + \sigma_A), \sigma_A/(\sigma_p + \sigma_\theta + \sigma_A)\}$.

## 5.2 Estimation result

The estimations of the structural parameters through indirect inference are reported in Table 4, for SOEs, NSOEs and FFEs, respectively.

Table 4: Estimation of structural parameters

| Definition for parameters | Parameters | SOEs | NSOEs | FFEs |
|---|---|---|---|---|
| Share of putty-clay investment | $\eta$ | 0.675 | 0.625 | 0.550 |
| | | (0.007) | (0.010) | (0.020) |
| Serial correlation of energy price $P_t^e$ | $\rho_P$ | 0.550 | 0.550 | 0.600 |
| | | (0.027) | (0.032) | (0.059) |
| Serial correlation of embodied technology $\theta_t$ | $\rho_\theta$ | 0.400 | 0.538 | 0.900 |
| | | (0.441) | (0.895) | (0.087) |
| Cross correlation between $P_t^e$ and $\theta_t$ | $\rho_{P\theta}$ | 0.200 | 0.050 | 0.100 |
| | | (0.038) | (0.067) | (0.212) |
| Serial correlation of disembodied technology $A_t$ | $\rho_A$ | 0.725 | 0.838 | 0.750 |
| | | (0.042) | (0.051) | (0.126) |
| Cross correlation between $P_t^e$ and $A_t$ | $\rho_{PA}$ | 0.200 | 0.200 | 0.200 |
| | | (0.012) | (0.013) | (0.035) |
| Relative standard deviation of innovation to $\theta_t$ | $\frac{\sigma_\theta}{\sigma_p+\sigma_\theta+\sigma_A}$ | 0.667 | 0.667 | 0.600 |
| | | (0.027) | (0.059) | (0.160) |
| Relative standard deviation of innovation to $A_t$ | $\frac{\sigma_A}{\sigma_p+\sigma_\theta+\sigma_A}$ | 0.111 | 0.111 | 0.200 |
| | | (0.004) | (0.007) | (0.058) |
| Objective function in indirect inference | $J(\hat{\psi})$ | 107.606 | 121.558 | 44.728 |

Note: standard errors are in parentheses. The 1% critical value for $J(\hat{\psi})$ is 45.642. Standard errors reported for $\frac{\sigma_\theta}{\sigma_p+\sigma_\theta+\sigma_A}$ are standard errors of $\sigma_\theta/\sigma_p$. Standard errors reported for $\frac{\sigma_A}{\sigma_p+\sigma_\theta+\sigma_A}$ are standard errors of $\sigma_A/\sigma_p$.

For all three types of firms, the magnitude of the proportion of output produced by putty-clay investment ranges from 0.55 to 0.68. These estimates are in line with Gilchrist and Williams [2000], in which their estimates of the share of putty-clay investment in the US economy during 1967 to 1997 ranges from 0.47 to 0.64 among their various models. Meanwhile, our estimates of $\eta$ are significantly different from 0, indicating that putty-clay investment also plays a significant role in explaining energy use by China's industrial firms. It indicates that new capital goods that embedded with energy-efficiency technology is a crucial channel through which firms reduce their energy intensity. For instance, Zhang and Huang [2017] find that utilization of the energy-efficient basic-oxygen furnace and phasing out the energy-inefficient open-hearth furnace is a key factor driving down the energy intensity in China's iron and steel industry from 1980 to 2015.Last, our estimates of $\eta$ show that SOEs have the highest proportion of putty-clay investment, while FFEs have the lowest proportion. This result is consistent with the stylized fact, based on Table 1, that the energy intensity of SOEs is relatively more inelastic in response to energy price change, while that of the FFEs is less inelastic.

Possible explanations regarding why SOEs exhibit a relatively large magnitude of $\eta$ include the following: first, energy prices for SOEs are less volatile for NSOEs and FFEs, so SOEs tend to invest in more putty-clay capital; second, SOEs receive investment subsidies that may be more targeted and generous to specific periods of energy price change; third, SOEs occupy industries with high entry cost, as documented in Li et al. [2015], specifically related to energy-intensive capital, so they may concentrate vintage investment and major capital renovation in times of entry; last, SOEs optimizing time horizon may be longer than that of other ownership types, shown as the case study of state-owned steel enterprise in Jin et al. [2017], since their levels of x-inefficiency are somewhat greater.

Table 4 also shows that the energy price is serially correlated, which is captured by $\rho_p$. Specifically, compared with SOEs and NSOEs, the energy prices of FFEs are relatively more serially correlated. In the AR(1) specification of the energy price, described in Eq. (9), our estimates of $\rho_p$ imply that the unconditional variance of the log of energy prices for SOEs is comparable to NSOEs, and largest for the FFEs. This result is consistent with what we observe from the firm-level data: the standard deviations of log energy prices for SOEs, NSOEs and FFEs are 1.48, 1.44 and 1.54, respectively.

The investment-specific technology, $\theta_t$, is also serially correlated, as $\rho_\theta$ ranges from 0.4 to 0.9. Although there is no prior expectation about the serial correlation of investment-specific technology, our estimates of $\rho_\theta$ are comparable to Greenwood et al. [2000], who estimate the AR(1) coefficient of investment-specific technology to be 0.64, based on an equipment price index constructed by Gordon [1990]. Gilchrist and Williams [2000] also estimate the AR(1) coefficient for investment-specific technology to be in the vicinity of 0.98 using US aggregate data from 1967-1997. This is somewhat higher than our estimates.

The estimates of $\rho_{p\theta}$ are positive for all three types of ownership. The positive estimate for $\rho_{p\theta}$ is an indication that capital-augmenting innovation is induced by energy prices. This finding is in line with Popp [2002], who reports a positive effect of energy prices on energy-efficient innovation using US patent data from 1970 to 1994. That the estimates of $\rho_{p\theta}$ are the largest for SOEs could result from government subsidies. When energy prices are rising, SOEs receive subsidies from government, thereby enabling SOEs to purchase efficient capital.

The estimates of $\rho_A$ indicate that the factor-neutral technology $A_t$ is also serially correlated, as $\rho_A$ ranges from 0.70 to 0.85. Although there is no clear prior for the serial correlation of factor neutral technology, our estimates of $\rho_A$ are in line with calibration or estimation exercises in real business cycle literature, i.e., DeJong and Dave [2011] and King and Rebelo [1999]. The estimates of $\rho_{pA}$ are positive for our three ownership types. The positive values of $\rho_{pA}$ indicate that innovation in the disembodied factor neutral technology is also induced by energy price change. When energy price rises, firms tend to choose a higher $A_t$, thereby reducing the firm's energy intensity.

That $\eta > 0$ and positive values in $\rho_{p\theta}$ and $\rho_{pA}$ suggest that firms would adopt both disembodied and embodied energy-efficient technology and invest in energy-saving capital in response to rising energy prices in China's industrial firms. This finding is in line with Alpanda and Peralta-Alva [2010], who find that U.S.

firms adopt energy-efficient technology and obsolescence of energy-consuming capital during the oil crisis of 1973-1974.

The relative magnitudes of $\sigma_\theta$ and $\sigma_A$ suggest that the investment-specific technology shock plays a relatively larger role in explaining the dynamics of energy intensity and investment. The relative importance of three shocks in the descending order are: investment-specific technology shock, energy price shock and disembodied technology shock for all three types of firms.

The last column of Table 4 reports the value of the objective function, $J(\hat{\psi})$ in Equation (11), which measures the difference between $g_M(\psi)$ and $g_d$. With the optimal weighting matrix $W$, the distribution of $J(\hat{\psi})$ converges to a $\chi^2(n-k)$ distribution, where $n$ is number of moments to be matched, and $k$ is number of parameters estimated in the structural model. For the structural model we estimated, at the 1% significance level, the critical values of a $\chi^2$ distribution with degree freedom of 26 (i.e., 34-8) is 45.642. This is not surprising that we reject a test of equality between the model moments $g_M(\psi)$ and the data moments $g_d$. One reason is that given the large sample size in the data, the regression coefficients are precisely measured, and consequently the weighting matrix $W$ has very large values, as large as magnitudes of $10^3$. This leads to a relatively large value in the objective function in Equation (11). Thus, given how precisely these micro-moments are calculated from the actual data, virtually any model would be formally rejected with even very modest deviations of the simulated moments from the data moments.[7]

To see how the model reproduces the regression coefficients reported in Tables 1- 3, we compare the regression results from the estimated model with those from actual firm-level data for SOEs, NSOEs and FFEs, respectively, in Tables 5,6 and 7. In Tables 5-7, the standard errors of the regression coefficients from the model and the data are not listed, because we focus on the regression coefficients other than the their standard errors. More importantly, we solve the model by first-order linear approximation, thus the standard deviation of energy price shock drops out in the decision rules. Consequently, the standard errors of coefficients are undetermined. [8]

The left panel labeled "Model" reports the regression coefficients from the model, and the right panel labeled "SOEs" reports regression coefficients for the SOEs, which are reported in panel A of Tables 1, 2, and 3. Our model is able to reproduce the inelastic response of energy intensity to energy prices, as the coefficients from Regression 1; it also reproduces the price-investment mechanism. The coefficients of $NVFA/OVFA$

[7]Large values in the objective function in indirect inference are not uncommon. In a variety of papers, topics including estimation of capital adjustment cost (Cooper and Haltiwanger [2006]), labor adjustment cost (Cooper et al. [2015]), the demand function for fish (Graddy and Hall [2011]), vintage capital and business cycle (Gilchrist and Williams [2000]), etc., the null hypothesis that the structural model is the true data generation process is overwhelmingly rejected.

[8]An extension of this analysis is to estimate the standard deviation of energy price shock, $\sigma_P$, along with other parameters, by matching the 34 regression coefficients and their standard errors in Equations (1), (2) and (3).

are all negative in Regression 2; for Regression 3, our model replicates three of the five positive estimates for the investment response. The fact that compared with the actual regression coefficients model estimates are somewhat negative for the first two periods and more robustly positive in the last two periods may result from a greater investment lag built into the investment response process in the model.

Table 5: Compare the model with data for SOEs

| | Model | | | | | SOEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) 1-year | (3) 2-year | (4) 3-year | (5) 4-year | (1) | (2) 1-year | (3) 2-year | (4) 3-year | (5) 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P^e_t$ | −0.405 | −0.277 | −0.278 | −0.278 | −0.279 | −0.389 | −0.304 | −0.325 | −0.313 | −0.304 |
| $P^e_{t-1}$ | | −0.238 | −0.159 | −0.160 | −0.159 | | −0.206 | −0.147 | −0.159 | −0.126 |
| $P^e_{t-2}$ | | | −0.145 | −0.093 | −0.094 | | | −0.141 | −0.087 | −0.129 |
| $P^e_{t-3}$ | | | | −0.095 | −0.061 | | | | −0.111 | −0.066 |
| $P^e_{t-4}$ | | | | | −0.064 | | | | | −0.081 |
| Regression 2: Energy intensity responding to the vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P^e_t$ | −0.403 | −0.277 | −0.282 | −0.299 | −0.315 | −0.387 | −0.303 | −0.323 | −0.324 | −0.318 |
| $\frac{NVFA}{OVFA}$ | −0.143 | −0.145 | −0.132 | −0.114 | −0.096 | −0.125 | −0.108 | −0.148 | −0.128 | −0.132 |
| Lagged $P^e$ | | −0.237 | −0.298 | −0.328 | −0.344 | | −0.205 | −0.285 | −0.339 | −0.379 |
| Regression 3: vintage structure $NVFA/OVFA$ responding to energy prices | | | | | | | | | | |
| Lagged $P^e$ | −0.002 | −0.003 | 0.015 | 0.048 | 0.090 | 0.012 | 0.013 | 0.031 | 0.040 | 0.059 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "SOEs" are regression results using actual SOE firm-level data, and these coefficients are also reported in the middle panels of Tables 1, 2 and 3.

For the NSOEs, Table 6 shows that the model imitates most coefficients from Regression 1 and Regression 2. For regression 3, the coefficients in columns (2)-(5) based on the model are very close to zero.

Table 6: Comparing the model with data for NSOEs

| | Model | | | | | NSOEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) 1-year | (3) 2-year | (4) 3-year | (5) 4-year | (1) | (2) 1-year | (3) 2-year | (4) 3-year | (5) 4-year |
| Regression 1: energy intensity responding to energy prices | | | | | | | | | | |
| $P^e_t$ | −0.448 | −0.322 | −0.323 | −0.323 | −0.324 | −0.441 | −0.339 | −0.351 | −0.330 | −0.315 |
| $P^e_{t-1}$ | | −0.233 | −0.147 | −0.148 | −0.148 | | −0.217 | −0.121 | −0.119 | −0.074 |
| $P^e_{t-2}$ | | | −0.158 | −0.094 | −0.095 | | | −0.178 | −0.134 | −0.137 |
| $P^e_{t-3}$ | | | | −0.118 | −0.069 | | | | −0.163 | −0.141 |
| $P^e_{t-4}$ | | | | | −0.089 | | | | | −0.048 |
| Regression 2: Energy intensity responding to vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P^e_t$ | −0.445 | −0.321 | −0.323 | −0.336 | −0.351 | −0.440 | −0.337 | −0.341 | −0.320 | −0.309 |
| $\frac{NVFA}{OVFA}$ | −0.144 | −0.148 | −0.142 | −0.131 | −0.118 | −0.106 | −0.160 | −0.180 | −0.227 | −0.215 |
| Lagged $P^e$ | | −0.233 | −0.303 | −0.344 | −0.372 | | −0.217 | −0.305 | −0.422 | −0.408 |
| Regression 3: vintage structure $NVFA/OVFA$ responding to lagged energy prices | | | | | | | | | | |
| Lagged $P^e$ | −0.007 | −0.012 | −0.001 | 0.025 | 0.062 | 0.010 | 0 | 0 | 0 | 0 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "NSOEs" are regression results using actual NSOE firm-level data, and these coefficients are also reported in the middle panels of Tables 1, 2 and 3. We report statistically insignificant coefficients as zeros.

Finally, for the FFEs, Table 7 compares the coefficients generated by the model with coefficients using the data for foreign firms. The model successfully reproduces the results obtained from the regressions.

Table 7: Comparing the model with data for FFEs

| | Model | | | | | FFEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) 1-year | (3) 2-year | (4) 3-year | (5) 4-year | (1) | (2) 1-year | (3) 2-year | (4) 3-year | (5) 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P_t^e$ | −0.519 | −0.387 | −0.388 | −0.388 | −0.389 | −0.525 | −0.425 | −0.404 | −0.360 | −0.467 |
| $P_{t-1}^e$ | | −0.224 | −0.147 | −0.147 | −0.147 | | −0.221 | −0.135 | −0.126 | 0 |
| $P_{t-2}^e$ | | | −0.130 | −0.078 | −0.079 | | | −0.155 | −0.095 | 0 |
| $P_{t-3}^e$ | | | | −0.088 | −0.052 | | | | −0.179 | −0.134 |
| $P_{t-4}^e$ | | | | | −0.061 | | | | | −0.089 |
| Regression 2: Energy intensity responding to vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P_t^e$ | −0.516 | −0.387 | −0.392 | −0.408 | −0.424 | −0.525 | −0.425 | −0.401 | −0.349 | −0.415 |
| $\frac{NVFA}{OVFA}$ | −0.055 | −0.056 | −0.055 | −0.052 | −0.049 | 0 | 0 | 0 | 0 | 0 |
| Lagged $P^e$ | | −0.223 | −0.274 | −0.297 | −0.310 | | −0.222 | −0.292 | −0.403 | −0.343 |
| Regression 3: Vintage structure $NVFA/OVFA$ responding to lagged energy price | | | | | | | | | | |
| Lagged $P^e$ | −0.007 | −0.011 | 0.002 | 0.028 | 0.065 | 0 | 0 | 0 | 0 | 0 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "FFEs" are regression results using actual foreign firm-level data, and these coefficients are also reported in the lower panels of Tables 1, 2 and 3. We report statistically insignificant coefficients as zeros.

In addition to the full model estimated in this section, we also estimate three alternative models. Each of the three models omits a certain element in our full model. In Table 8, we compare results for our full model developed in Section 4 with the three alternative models. The detailed specification and estimation results of these three alternative models are presented in the Appendix C. The three alternative models are: (i) the basic model for which the sole source of shocks is energy prices (column 1 labeled as "Without $\theta_t$ nor $A_t$" in Table 8), (ii) the Extended I model, which adds only investment-specific technology $\theta_t$ , with the results reported in column 2 labeled as "with $\theta_t$ only" in Table 8, and (iii) the Extended II model with disembodied factor-neutral technology shocks alone, as reported in column 3 labeled as "with $A_t$ only" in Table 8. Similarly, the results for our full model are shown in column 4 labeled as "With both $\theta_t$ and $A_t$" in Table 8. Table 8 shows how each of the models fits with the regression results in Section 3, as determined by the comparative values of $J(\hat{\psi})$, which measure the distance between regression coefficients based on the model and coefficients based on actual data.

Table 8: Comparison among models

| $J(\hat{\psi})$ | Without $\theta_t$ nor $A_t$ | with $\theta_t$ only | with $A_t$ only | With both $\theta_t$ and $A_t$ |
|---|---|---|---|---|
| SOEs | 2453.093 | 321.710 | 543.763 | 107.606 |
| NSOEs | 1420.000 | 248.905 | 481.787 | 121.558 |
| FFEs | 429.752 | 89.280 | 105.157 | 44.738 |
| 1% Critical Values | 53.486 | 49.588 | 49.588 | 45.642 |

In terms of $J(\hat{\psi})$, we first notice that our full model provides a significantly better match than any of the other three models. Second, adding investment-specific technology or disembodied technology substantially improves the fit of the model as compared with the basic model. Third, all four models tend to have a better fit for FFEs firms than SOEs and NSOEs.

Although it is rejected by the $J$-test (except for FFEs), our model still fundamentally mimics the stylized facts. While we might wish for the model to replicate the exact coefficient estimates reported in Tables 1, 2, and 3, as Prescott [1986] pointed out: "The models constructed within this theoretical framework are necessarily highly abstract. Consequently, they are necessarily false, and statistical hypothesis testing will reject them. This does not imply, however, that nothing can be learned from such quantitative theoretical exercise." In Section 6, we conduct some policy experiment based on our model.

# 6 A counterfactual

The advantage of having a structural model is that we are able to conduct policy experiments or create counterfactual, which are not available in reduced-form regression analysis. In this section, we conduct one policy experiment: if the Chinese government limits its preferential treatment to SOEs, such as monopoly power, subsidies, and easy access to external funds, so that SOEs act more like FFEs, how will it alter the SOEs' energy intensity response to rising energy price? In particular, we alter one parameter in this exercise; that is, we change $\eta$, so that the SOE share of putty-clay investment decrease from 0.675 to 0.550, the estimated share of putty-clay investment for FFEs. All the other parameter values remain unchanged, thus sustaining some differentiating characteristics of SOEs versus FFEs. These differences may be sustained by differences in industry type, by provincial location, including local policies, and other factors, including governance structures, not directly related to central government policy, which we assume is principally responsible for differences in the putty-clay vintage composition of investment.

Table 9: Effect of SOEs reform on energy intensity

| Year | % change in energy intensity for unreformed SOEs with $\eta = 0.675$ | % change in energy intensity for reformed SOEs with $\eta = 0.550$ |
|---|---|---|
| T | −27.56 | −37.78 |
| T+1 | −28.76 | −34.21 |
| T+2 | −23.67 | −26.02 |
| T+3 | −18.84 | −19.72 |
| T+4 | −14.63 | −14.85 |
| T+5 | −11.13 | −11.08 |
| T+6 | −8.30 | −8.17 |
| T+7 | −6.04 | −5.93 |
| T+8 | −4.27 | −4.20 |
| T+9 | −2.90 | −2.87 |

Note: energy price rises by 50% in year T.

Table 9 compares the percentage changes in energy intensity under the reformed and unreformed scenarios when energy price rises by 50%. As shown below, at the onset of energy price shock, energy intensity for reformed SOEs is expected to decrease by 37.78%, almost 10% more than that for the non-reformed SOEs. The difference response in energy intensity tends to be small after four years. This difference is not surprising. With diminished motivation for and access to investment in putty-clay vintages, SOEs rely more on disembodied means of energy conservation. Moreover, government investment subsidies tied to energy policy are less important. If subsides do persist, they may be more factor-neutral or biased toward other objectives, including employment and exports. In any event, this counterfactual simulation shows that energy-specific vintage capital matters for SOEs. In the short-term following energy price increases, the reliance on putty-clay investment appears to substitute for other measures as a means for reducing energy intensity.

## 7 Conclusion

This paper uses a novel approach to uncover the dynamic relationships among energy price, energy intensity and investment. We formulate and estimate a structural model that successfully mimics the observed stylized facts generated from the commonly-used energy intensity-price regression equations. These widely-used regression equation can be interpreted as the reduced form equation derived from the DSGE model we have devised and estimated using the stylized facts of different price-energy responses across ownership types in Chinese industry.

A key innovation that enables this exercise is our data set that allows us to compute the age structure of the capital stock of each firm, for which we are able to identify the energy efficiency of different vintages across the three key ownership types – state, non-state, and foreign owned enterprises.

Our analysis demonstrates that the vintage capital that embodied energy efficiency plays a critical role in achieving energy efficiency for China's industrial firms. We find that the model with vintage capital or putty-clay investment does a better job of replicating the dynamics between energy prices and energy intensity than do the models without putty-clay investment.

Our key findings are: first, the DSGE model that combines putty-clay and putty-putty investment, and incorporating both embodied investment-specific technology and disembodied factor-neutral technology provides the best match with the stylized facts. Second, SOEs retain the largest share of putty-clay vintage capital; the NSOE share follows; the FEEs exhibits the least, as this latter group of firms dedicates a majority of its investment to putty-putty vintages of capital.

We posit that these differences arise principally from two conditions. The first is that the government appears to smooth energy prices for the SOE sector. The second is that subsidized capital is more widely available to the state-owned sector than it is to other firm types.

Given these empirical findings, we conclude that with greater price stability and financial subsidies for replacing the most outdated inefficient vintages of capital, SOEs appear to be making optimizing vintage selections, as do the NSOEs and FFEs whose energy price-investment decision are shaped more by market-based energy price and constrained financial market conditions. When we simulate the estimation of the policy presences for SOEs by the vintage investment behavior of SOEs and FFEs to be equivalent, we find that in response to rising energy prices, SOEs exhibit a substantially higher rate of near-term energy conservation.

These findings have several important implications. First, any policy that distorts investment incentives will have a substantially larger effect when technology is embodied in capital goods. Second, conflicts in current trade between China and the US, and perhaps other countries, may create barriers for Chinese firms to import equipment that inhibits the diffusion of embodied energy-saving technologies. Lastly, heavy reliance on putty-clay investment for adjusting to higher energy prices, as with SOEs, suggests asymmetric responses of the aggregate economy to energy price shocks. Due to the negative output effects, recessions caused by large increases in energy prices are deeper than expansions caused by the same proportional reduction in energy price. Avoiding large increases in energy prices by stocking domestic energy supplies or decreasing the dependence of imported energy could alleviate the negative impacts of rising energy prices on the aggregate economy.

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# Appendix

## A. Related research on China's energy intensity

Table 10: Related research on China's energy intensity

| Authors | Period | Data | Methodology | Driving factors |
|---|---|---|---|---|
| **The decomposition method** | | | | |
| Fisher-Vanden et al. [2004] | 1997-1999 | Firm-level data | Index decomposition analysis (Divisia index) | Shift in industrial structure, Reduction in firm-level energy intensity |
| Ma and Stern [2008] | 1980-2003 | Sector-level data (primary, secondary, tertiary industries and households) | Index decomposition analysis (logarithmic mean Divisia index) | Technical change, structural change, Inter-fuel substitution |
| Wu [2012] | 1997-2007 | Province-level data | Index decomposition analysis (Divisia index) | Efficiency effect, structural effect |
| Wang et al. [2018] | 2003-2015 | Industry-level data (36 industry sectors) | Index decomposition analysis (logarithmic mean Divisia index) | R&D expenditure, investment |
| Tan and Lin [2018] | 2000-2013 | Industry-level data (4 energy-intensive industries) | Index decomposition analysis, Production decomposition analysis | Technology improvement effect, Capital-energy substitution effect |
| **The regression method** | | | | |
| Fisher-Vanden et al. [2004] | 1997-1999 | Firm-level panel data | Regressions: SUR | Energy prices, R&D expenditures, ownership reform |
| Hang and Tu [2007] | 1985-2004 | National-level time series data | Regressions: SUR | Energy prices, sectoral shifts |
| Wu [2012] | 1997-2007 | Province-level data | Regressions analysis | Income per capita, energy price; KL ratio, growth rate of capital stock |
| Herrerias et al. [2013] | 1985-2008 | Province-level regional data | Regression analysis | Different types of investment (foreign direct investment, state investment, domestic non-state investment); Import, share of industry, energy prices |
| Yang et al. [2016] | 1985-2012 | Province-level data | Regression analysis | Total population, energy price index |
| Fisher-Vanden et al. [2016] | 1997-2004 | Firm-level panel data on four industries | Regressions (OLS, Fixed Effect) | Energy price, technology development expenditure, Ownership effect, economies of scale |
| Li and Lin [2016] | 1985-2012 | Industry-level data on 6 productive sectors | Regression (two-stage dynamic adjustment model) | Labor substitution, energy price; Technology embodied in capital is carbon-intensive |
| Bu et al. [2019] | 2005-2007 | Firm-level data in Jiangsu Province of China | Regression analysis | Foreign Direct Investment (FDI), Technology absorptive capacity |
| Huang et al. [2020] | 2000-2014 | Province-level data | Regression analysis (dynamic adjustment model) | Domestic R&D; spillover from FDI; Structural change |

## B. Model solution and estimation

### B1. Calibration

Before solving and simulating the model, we calibrate parameter values in preference and production technology. The calibrated parameter values are presented in Table 11.

Table 11: Predefined parameters in the model

| Meaning of parameter | Parameter | Value |
|---|---|---|
| **Preference** | | |
| Annual discount rate | $\beta$ | 0.98 |
| Relative risk aversion in utility | $\gamma$ | 1.5 |
| Leisure parameter in utility | $\phi$ | 3 |
| **Production** | | |
| Share of capital in production function | $\lambda\alpha$ | 0.52 |
| Share of labor in production function | $1-\alpha$ | 0.31 |
| Annual depreciation rate for capital | $\delta$ | 0.10 |
| Life span of capital | $M$ | 15 |
| Standard deviation of $\theta_{it}$ | $\sigma$ | 0.25 |

The calibrated values of the predefined parameters are frequently used in the literature. The annual discount rate $\beta = 0.98$. In the utility function $\frac{[C_t(1-L_t)^{\phi}]^{1-\gamma}}{1-\gamma}$, we set the coefficient of the relative risk aversion to $\gamma = 1.5$. The leisure parameter $\phi$ is set to 3, which implies that in the steady state, households work about 23% of their time, which is generally consistent with a 40-hour week adjusted for sleep, holidays and vacations.

In the production function $Y = (K^{\lambda} En^{1-\lambda})^{\alpha} L^{1-\alpha}$, $\lambda$ is set to be 0.757, and $\alpha$ is set to be 0.689. Together these values imply a labor share of income $(1-\alpha)$ of 0.3112, an energy share of income $(1-\lambda)\alpha$ of 0.17, and a capital share of income $(\lambda\alpha)$ of 0.52. These are consistent with the average factor shares for the firm-level data; the capital share of 0.52 is also consistent with Bai et al. [2006] and Song et al. [2011].

The annual depreciation rate for capital is $\delta = 0.10$, which is also used in Song et al. [2011] and David and Venkateswaran [2019]. The number of vintages, $M$, is set to be 15 years. In fact, in manufacturing industries, the life-span of equipment and machines varies significantly. The minimum life-span for depreciation dictated by the general accounting rule is 10 years.[9] Here we use 15 years as the average life-span of capital across all industries. $M = 15$ is also used in Wei [2003].

There is no prior estimate for the standard deviation of the idiosyncratic uncertainty, $\sigma$. For the calibration, we use $\sigma = 0.25$ , which has been used in Wei [2003] and Gilchrist and Williams [2000].

[9] For more detail, please see http://www.gov.cn/gongbao/content/2008/content_859860.htm.

### B2. Computational strategy

First, the two-sector DSGE model described in Section 4 is solved by Dynare. The decision rules are obtained by linearizing the first-order conditions, following the method described in Blanchard and Kahn [1980]. We also solve the model using the second-order approximation and the extended deterministic path method (see Fair and Taylor [1983]).These methods are able to conserve the non-linearity in the decision rules, in comparison to the first-order approximation or linearization. The decision rules using the alternative two methods are similar to those obtained through the first-order linearization. Thus, the gain in decision rule's accuracy is limited. To save computational time in the indirect inference estimation routine, we solve the DSGE model through first-order linearization.

Second, using the decision rules obtained from the first step, we simulate a synthetic data with 250 time periods and 300 firms. Then we run the same three sets of regression described in Equations (1), (2)and (3) on the synthetic data. These regression coefficients, $g_M(\psi)$, are used to compare with the regression coefficients, $g_d$, which are obtained directly from the firm-level data. As the process is ergodic (after discarding the first 50 periods), the regression coefficients from the simulated data are determined by the total observations.

Last, we find the minimum value of the objective function in Equation (11) using a grid search. The standard errors of estimated parameters are calculated numerically (see Hayashi [2000]).

### B3. Mapping of parameters $\psi$ to regression coefficients $g_M$

We estimate the model parameter vector $\psi = \{\eta, \rho_p, \rho_\theta, \rho_{p\theta}, \rho_A, \rho_{pA}, \sigma_\theta/(\sigma_p + \sigma_\theta + \sigma_A), \sigma_A/(\sigma_p + \sigma_\theta + \sigma_A)\}$ by minimizing the distance between $g_M(\psi)$ and $g_d$, where $g_M(\psi)$ is the model analogue of $g_d$. To establish the fact that $g_M$ is a function of $\psi$, we rely on the fact that our model solution is linear and may be expressed in the standard state-space form:

$$
\begin{aligned}
S_t &= A(\psi)S_{t-1} + B(\psi)U_t \\
X_t &= F(\psi)S_t
\end{aligned}
$$

where $(U_t U_t^T) = I$ , $S_t$ is a vector of the state variables in this model and $X_t$ is a vector of observable variables in the model.

Specifically, $U_t$ is a vector of 3 structural shocks in the model: shock to energy price, shock to embodied technology and shock to disembodied technology. The state variables in $S_t$ are: energy price, $P_t^e$, disembodied technology, $A_t$, embodied technology, $\theta_t$, investment in putty-putty sector for each $M$ vintage, $k_{t-j}, j = 1, 2, \ldots, M$; investment in putty-clay sector for each $M$ vintage, $k_{t-j}, e_{t-j}, q_{t-j}, j = 1, 2, \ldots, M$. The observable variables in $X_t$ include: energy intensity, $En_t/Y_t$, capital vintage structure $NVFA_t/OVFA_t$, and lagged or moving average of lagged energy prices $P^e_{t-j}, i = 1, 2, 3, 4$. The model solution proposes a data generation process for energy intensity, $En_t/Y_t$, capital vintage structure $NVFA_t/OVFA_t$, and energy price $P^e_t$. Then 3 sets of regressions are run based on $En_t/Y_t$, $NVFA_t/OVFA_t$ and $P^e_t$ . This indicates that the regression coefficients $g_M$ may then be computed as a function of $A$, $B$ and $F$. Because the matrices $A$, $B$ and $F$ are (nonlinear intractable) functions of the underlying model parameters $\psi$, the vector of regression coefficients $g_M$ is also a function of $\psi$.

Last, because we solve this model by linearizing all the first-order conditions, the regression coefficients in model depend on the relative magnitude of standard deviations of 3 structural shocks, i.e., $\sigma_\theta/(\sigma_p + \sigma_\theta + \sigma_A), \sigma_A/(\sigma_p + \sigma_\theta + \sigma_A)$, not the absolute values of $\sigma_p, \sigma_\theta, \sigma_A$.

## C. Estimation results of alternative models

### C1. Benchmark model

In this section, we estimate the model, in which energy price shock is the only shock; or equivalently, we shut down both terms $\theta_t$ and $A_t$. We refer the model with energy price shock only as the benchmark model. In another way of saying, we set $\rho_\theta = \rho_{p\theta} = \rho_A = \rho_{pA} = 0$, and only estimate the values of $(\eta, \rho_P)$ in the benchmark model.

The estimations of $(\eta, \rho_P)$ for SOEs, NSOEs and FFEs are reported in Table 12. First, in comparison to SOEs and NSOEs, as expected, FFEs have a lower proportion of putty-clay investment; second, for three types of firms, their energy prices are not serially correlated, $\rho_p$ ranges from $-0.09$ to $0.139$; The reason $\rho_p$ is small in magnitude is that now we force the benchmark model to match the coefficients in Regression 2 and Regression 3, which capture the price-investment mechanism. If $\rho_p$ is relatively high, then the coefficients of $NVFA/OVFA$ in Regression 2 are either positive or very negative, and coefficients from Regression 3 are all negative. In order the match coefficients observed from actual data, the best match of $\rho_p$ is close to zero in magnitude. Third, the values of $J(\hat{\psi})$ reported in Table E4 increase dramatically, in comparison to Table 4. This is because we set the benchmark model to match coefficients from all three sets of regressions.

Table 12: Estimation of structural parameters in benchmark model

| Definition for parameters | Parameters | SOEs | NSOEs | FFEs |
|---|---|---|---|---|
| Share of putty-clay investment | $\eta$ | 0.535 | 0.485 | 0.401 |
| | | (0.005) | (0.006) | (0.009) |
| Serial correlation of energy price $P_t^e$ | $\rho_P$ | −0.080 | −0.090 | 0.139 |
| | | (0.029) | (0.024) | (0.043) |
| Objective function in indirect inference | $J(\hat{\psi})$ | 2453 | 1420 | 429 |

Note: standard errors are in parentheses. The 1% critical value for $J(\hat{\psi})$ is 53.486.

In Tables 13, 14 and 15, we compare the benchmark model based on the estimates in Table 12, with data from SOEs, NSOEs and FFEs, respectively. In order to match the coefficients in Regression 2 and Regression 3, the energy price cannot be highly serially correlated. This also leads to the coefficients of lagged energy prices in Regression 1 close to zero, while those coefficients are significantly negative from actual data.

Table 13: Comparing benchmark model with data for SOEs

| | Model | | | | | SOEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| | | 1-year | 2-year | 3-year | 4-year | | 1-year | 2-year | 3-year | 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P_t^e$ | −0.422 | −0.422 | −0.421 | −0.421 | −0.421 | −0.389 | −0.304 | −0.325 | −0.313 | −0.304 |
| $P_{t-1}^e$ | | 0.004 | 0.005 | 0.005 | 0.005 | | −0.206 | −0.147 | −0.159 | −0.126 |
| $P_{t-2}^e$ | | | 0.001 | 0.001 | 0.001 | | | −0.141 | −0.087 | −0.129 |
| $P_{t-3}^e$ | | | | 0.001 | 0.001 | | | | −0.111 | −0.066 |
| $P_{t-4}^e$ | | | | | 0.001 | | | | | −0.081 |
| Regression 2: Energy intensity responding to vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P_t^e$ | −0.422 | −0.422 | −0.422 | −0.422 | −0.422 | −0.387 | −0.303 | −0.323 | −0.324 | −0.318 |
| $\frac{NVFA}{OVFA}$ | −0.082 | −0.028 | −0.033 | −0.036 | −0.041 | −0.125 | −0.108 | −0.148 | −0.128 | −0.132 |
| Lagged $P^e$ | | 0.004 | 0.004 | 0.004 | 0.004 | | −0.205 | −0.285 | −0.339 | −0.379 |
| Regression 3: vintage structure $NVFA/OVFA$ responding to energy prices | | | | | | | | | | |
| Lagged $P^e$ | 0.001 | −0.019 | −0.036 | −0.050 | −0.063 | 0.012 | 0.013 | 0.031 | 0.040 | 0.059 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labelled "SOE" are regression results using actual SOE firm-level data, and these coefficients are also reported in the upper panels of Tables 1, 2 and 3.

Table 14: Comparing benchmark model with data for NSOEs

| | Model | | | | | NSOEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| | | 1-year | 2-year | 3-year | 4-year | | 1-year | 2-year | 3-year | 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P_t^e$ | $-0.470$ | $-0.469$ | $-0.469$ | $-0.469$ | $-0.469$ | $-0.441$ | $-0.339$ | $-0.351$ | $-0.330$ | $-0.315$ |
| $P_{t-1}^e$ | | 0.006 | 0.006 | 0.006 | 0.006 | | $-0.217$ | $-0.121$ | $-0.119$ | $-0.074$ |
| $P_{t-2}^e$ | | | 0.001 | 0.001 | 0.001 | | | $-0.178$ | $-0.134$ | $-0.137$ |
| $P_{t-3}^e$ | | | | 0.001 | 0.001 | | | | $-0.163$ | $-0.141$ |
| $P_{t-4}^e$ | | | | | 0.001 | | | | | $-0.048$ |
| Regression 2: Energy intensity responding to vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P_t^e$ | $-0.470$ | $-0.469$ | $-0.470$ | $-0.470$ | $-0.470$ | $-0.440$ | $-0.337$ | $-0.341$ | $-0.320$ | $-0.309$ |
| $\frac{NVFA}{OVFA}$ | $-0.098$ | $-0.029$ | $-0.039$ | $-0.043$ | $-0.052$ | $-0.106$ | $-0.160$ | $-0.180$ | $-0.227$ | $-0.215$ |
| Lagged $P^e$ | | 0.005 | 0.005 | 0.005 | 0.005 | | $-0.217$ | $-0.305$ | $-0.422$ | $-0.408$ |
| Regression 3: vintage structure $NVFA/OVFA$ responding to lagged energy prices | | | | | | | | | | |
| Lagged $P^e$ | 0.001 | $-0.019$ | $-0.036$ | $-0.050$ | $-0.063$ | 0.010 | 0 | 0 | 0 | 0 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "NSOEs" are regression results using actual NSOEs firm-level data, and these coefficients are also reported in the middle panels of Tables 1, 2 and 3. We report statistically insignificant coefficients as zeros.

Table 15: Comparing benchmark model with data for FFEs

| | Model | | | | | FFEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| | | 1-year | 2-year | 3-year | 4-year | | 1-year | 2-year | 3-year | 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P_t^e$ | $-0.549$ | $-0.548$ | $-0.548$ | $-0.548$ | $-0.548$ | $-0.525$ | $-0.425$ | $-0.404$ | $-0.360$ | $-0.467$ |
| $P_{t-1}^e$ | | $-0.008$ | $-0.008$ | $-0.008$ | $-0.007$ | | $-0.221$ | $-0.135$ | $-0.126$ | 0 |
| $P_{t-2}^e$ | | | $-0.001$ | $-0.001$ | $-0.001$ | | | $-0.155$ | $-0.095$ | 0 |
| $P_{t-3}^e$ | | | | $-0.001$ | $-0.001$ | | | | $-0.179$ | $-0.134$ |
| $P_{t-4}^e$ | | | | | $-0.001$ | | | | | $-0.089$ |
| Regression 2: Energy intensity responding to the vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P_t^e$ | $-0.549$ | $-0.548$ | $-0.549$ | $-0.549$ | $-0.549$ | $-0.525$ | $-0.425$ | $-0.401$ | $-0.349$ | $-0.415$ |
| $\frac{NVFA}{OVFA}$ | 0.107 | 0.029 | 0.024 | 0.031 | 0.041 | 0 | 0 | 0 | 0 | 0 |
| Lagged $P^e$ | | $-0.007$ | $-0.007$ | $-0.007$ | $-0.007$ | | $-0.222$ | $-0.292$ | $-0.403$ | $-0.343$ |
| Regression 3: Vintage structure $NVFA/OVFA$ responding to lagged energy price | | | | | | | | | | |
| Lagged $P^e$ | $-0.003$ | $-0.023$ | $-0.041$ | $-0.056$ | $-0.069$ | 0 | 0 | 0 | 0 | 0 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "Foreign" are regression results using actual foreign firm-level data, and these coefficients are also reported in the lower panels of Tables 1, 2 and 3. We treat statistically insignificant coefficients as zeros.

In sum, the benchmark model, in which energy price is the only shock, has difficulty to match coefficients from all 3 sets of regressions. To improve the fitness of model, we will add other shocks to the model, such as investment-specific technology shock of factor-neutral technology shock, so the extended models are able to replicates 3 sets of regression coefficients.

### C2. Extended I model

In this section, we estimate the model, which includes energy price shock and the investment-specific technology$\theta_t$; or equivalently, we shut down the disembodied technology term $A_t$. We refer this model as extended I model, or a model with embodied technology shock only. In another way of saying we set $\rho_A = \rho_{pA} = \sigma_A = 0$, and only estimate the four parameters, $(\eta, \rho_P, \rho_\theta, \rho_{p\theta}, \sigma_\theta/(\sigma_p + \sigma_\theta))$, in this extended model.

Including investment-specific technology or capital-augmented technology shock, the estimation of five structural parameters, $\{\eta, \rho_P, \rho_\theta, \rho_{p\theta}, \sigma_\theta/(\sigma_p + \sigma_\theta)\}$, in this extended I model are reported in Table 16, for SOEs, NSOEs and FFEs, respectively.

Table 16: Estimation of structural parameters in extended I model

| Definition for parameters | Parameters | SOEs | NSOEs | FFEs |
|---|---|---|---|---|
| Share of putty-clay investment | $\eta$ | 0.630 | 0.640 | 0.560 |
| | | (0.007) | (0.010) | (0.013) |
| Serial correlation of energy price $P_t^e$ | $\rho_P$ | 0.840 | 0.880 | 0.890 |
| | | (0.005) | (0.004) | (0.006) |
| Serial correlation of embodied technology $\theta_t$ | $\rho_\theta$ | 0.870 | 0.850 | 0.910 |
| | | (0.029) | (0.098) | (0.248) |
| Cross correlation between $P_t^e$ and $\theta_t$ | $\rho_{P\theta}$ | 0.440 | 0.200 | 0.180 |
| | | (0.035) | (0.027) | (0.022) |
| Relative standard deviation of innovation to $\theta_t$ | $\frac{\sigma_\theta}{\sigma_p+\sigma_\theta}$ | 0.545 | 0.643 | 0.706 |
| | | (0.008) | (0.003) | (0.011) |
| Objective function in indirect inference | $J(\hat{\psi})$ | 321.7103 | 248.905 | 66.645 |

Note: standard errors are in parentheses. The 1% critical value for $J(\hat{\psi})$ is 49.588. Standard errors reported for $\frac{\sigma_A}{\sigma_p+\sigma_A}$ are standard errors of $\sigma_\theta/\sigma_p$.

To see how the extended model reproduces the stylized facts, i.e., the long-run price and price-investment mechanism, we compare the regression results from the estimated model with those from actual firm-level data for SOEs, NSOEs and FFEs, respectively, in Tables 17, 18 and 19.

Table 17 reports the coefficients generated by the extended model using SOEs data. Adding the investment-specific technology shock into the model, the extended model is able to reproduce the coefficients from the sets of regressions, described by Equations (1), (2) and (3) in Section 3.

Table 17: Comparing extended I model with data for SOEs

| | Model | | | | | SOEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| | | 1-year | 2-year | 3-year | 4-year | | 1-year | 2-year | 3-year | 4-year |
| Regression 1: energy intensity responding to energy prices | | | | | | | | | | |
| $P^e_t$ | −0.443 | −0.284 | −0.286 | −0.285 | −0.286 | −0.389 | −0.304 | −0.325 | −0.313 | −0.304 |
| $P^e_{t-1}$ | | −0.195 | −0.103 | −0.105 | −0.104 | | −0.206 | −0.147 | −0.159 | −0.126 |
| $P^e_{t-2}$ | | | −0.111 | −0.027 | −0.029 | | | −0.141 | −0.087 | −0.129 |
| $P^e_{t-3}$ | | | | −0.102 | −0.025 | | | | −0.111 | −0.066 |
| $P^e_{t-4}$ | | | | | −0.092 | | | | | −0.081 |
| Regression 2: Energy intensity responding to the vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P^e_t$ | −0.438 | −0.286 | −0.290 | −0.302 | −0.313 | −0.387 | −0.303 | −0.323 | −0.324 | −0.318 |
| $\frac{NVFA}{OVFA}$ | −0.139 | −0.136 | −0.129 | −0.119 | −0.107 | −0.125 | −0.108 | −0.148 | −0.128 | −0.132 |
| Lagged $P^e$ | | −0.189 | −0.204 | −0.207 | −0.210 | | −0.205 | −0.285 | −0.339 | −0.379 |
| Regression 3: Vintage structure $NVFA/OVFA$ responding to energy prices | | | | | | | | | | |
| Lagged $P^e$ | 0.020 | 0.026 | 0.043 | 0.071 | 0.109 | 0.012 | 0.013 | 0.031 | 0.040 | 0.059 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "SOEs" are regression results using actual SOEs firm-level data, and these coefficients are also reported in the upper panels of Tables 1, 2 and 3.

For NSOEs, the extended model with investment-specific technology shocks can basically reproduce the stylized facts in all three sets of regressions. Table 18 shows that energy intensity is inelastic to current energy price changes, and significantly negative coefficients of past energy prices; in Regression 2, the coefficients of $NVFA/OVFA$ are significantly negative, although the magnitude are slightly larger. The extended model with investment-specific technology has some difficulty replicating the Regression 3. In Table 18, this estimated model generates a negative coefficient -0.018 in column (1) specification, whereas the NSOEs data shows that this coefficient is significantly positive.

Table 18: Comparing extended I model with data for NSOEs

| | Model | | | | | NSOEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| | | 1-year | 2-year | 3-year | 4-year | | 1-year | 2-year | 3-year | 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P^e_t$ | −0.519 | −0.302 | −0.304 | −0.304 | −0.305 | −0.441 | −0.339 | −0.351 | −0.330 | −0.315 |
| $P^e_{t-1}$ | | −0.250 | −0.090 | −0.093 | −0.091 | | −0.217 | −0.121 | −0.119 | −0.074 |
| $P^e_{t-2}$ | | | −0.181 | −0.038 | −0.041 | | | −0.178 | −0.134 | −0.137 |
| $P^e_{t-3}$ | | | | −0.162 | −0.034 | | | | −0.163 | −0.141 |
| $P^e_{t-4}$ | | | | | −0.144 | | | | | −0.048 |
| Regression 2: Energy intensity responding to the vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P^e_t$ | −0.518 | −0.303 | −0.290 | −0.295 | −0.305 | −0.440 | −0.337 | −0.341 | −0.320 | −0.309 |
| $\frac{NVFA}{OVFA}$ | −0.176 | −0.184 | −0.182 | −0.173 | −0.159 | −0.106 | −0.160 | −0.180 | −0.227 | −0.215 |
| Lagged $P^e$ | | −0.248 | −0.283 | −0.296 | −0.303 | | −0.217 | −0.305 | −0.422 | −0.408 |
| Regression 3: Vintage structure $NVFA/OVFA$ responding to lagged energy prices | | | | | | | | | | |
| Lagged $P^e$ | −0.018 | −0.020 | −0.019 | −0.014 | −0.007 | 0.010 | 0 | 0 | 0 | 0 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "NSOEs" are regression results using actual NSOEs firm-level data, and these coefficients are also reported in the middle panels of Tables 1, 2 and 3. We treat statistically insignificant coefficients as zeros.

Table 19 compares the coefficients generated by the extended model with coefficients using the data for the FFEs. The extended model is able to reproduce the coefficients from the energy price effect regressions. In Column (5), the coefficients of $P^e_{t-1}$ and $P^e_{t-2}$, generated from the model, are not exactly zero, but the two coefficients, -0.079 and -0.040, both fall within the 95% confidence intervals of the estimates using the FFEs data.[10] For Regression 2, as shown in Table E1, the coefficients of $P^e_t$ and lagged energy prices generated by the model are quite similar to the coefficients using the data for the foreign firms. For all specifications, the coefficients of $NVFA/OVFA$ generated from the model all fall within the 95% confidence intervals of the coefficients estimated from the actual data.[11] For Regression 3, the coefficients of lagged energy prices from the model are close to zero, although all the coefficients in Columns (1)-(5) from the model lie outside the 95% confidence intervals for the estimates using the data for the FFEs. [12]

Table 19: Comparing extended I model with data for FFEs

| | Model | | | | | FFEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| | | 1-year | 2-year | 3-year | 4-year | | 1-year | 2-year | 3-year | 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P^e_t$ | −0.615 | −0.394 | −0.397 | −0.396 | −0.398 | −0.525 | −0.425 | −0.404 | −0.360 | −0.467 |
| $P^e_{t-1}$ | | −0.248 | −0.078 | −0.081 | −0.079 | | −0.221 | −0.135 | −0.126 | 0 |
| $P^e_{t-2}$ | | | −0.188 | −0.037 | −0.040 | | | −0.155 | −0.095 | 0 |
| $P^e_{t-3}$ | | | | −0.168 | −0.033 | | | | −0.179 | −0.134 |
| $P^e_{t-4}$ | | | | | −0.149 | | | | | −0.089 |
| Regression 2: Energy intensity responding to the vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P^e_t$ | −0.606 | −0.394 | −0.376 | −0.377 | −0.384 | −0.525 | −0.425 | −0.401 | −0.349 | −0.415 |
| $\frac{NVFA}{OVFA}$ | −0.012 | −0.007 | −0.017 | −0.023 | −0.026 | 0 | 0 | 0 | 0 | 0 |
| Lagged $P^e$ | | −0.241 | −0.279 | −0.295 | −0.304 | | −0.222 | −0.292 | −0.403 | −0.343 |
| Regression 3: Vintage structure $NVFA/OVFA$ responding to lagged energy prices | | | | | | | | | | |
| Lagged $P^e$ | −0.048 | −0.053 | −0.057 | −0.060 | −0.062 | 0 | 0 | 0 | 0 | 0 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "Foreign" are regression results using actual foreign firm-level data, and these coefficients are also reported in the lower panels of Tables 1, 2 and 3. We treat statistically insignificant coefficients as zeros.

### C3. Extended II model

In this section, we estimate the model, which includes energy price shock and disembodied technology, $A_t$; or equivalently, we shut down the investment-specific technology, $\theta_t$. We refer the model as extended II model, or a model with disembodied technology shock only. In another way of saying we set $\rho_\theta = \rho_{p\theta} = \sigma_\theta = 0$, and only estimate the values of $(\eta, \rho_P, \rho_A, \rho_{pA}, \sigma_A/(\sigma_p + \sigma_A)$ in this extended model.

[10] 95% confidence intervals for coefficients of $P^e_{t-1}$ and $P^e_{t-2}$ in column (5) specification are:[-0.218, 0.222], [-0.187, 0.037], respectively.

[11] 95% confidence intervals for coefficients of $NVFA/OVFA$ in column2 (1)-(5) are: [-0.021, 0.129], [-0.069, 0.094], [-0.082, 0.109], [-0.092, 0.128], and [-0.127, 0.229].

[12] 95% confidence intervals for coefficients of $NVFA/OVFA$ from step-two regressions are: [-0.011, 0.016], [-0.018, 0.024], [-0.040, 0.016], [-0.058, 0.029], and [-0.047, 0.058].

We estimate the five structural parameters $(\eta, \rho_P, \rho_A, \rho_{pA}, \sigma_A/(\sigma_p + \sigma_A)$ together in the extended II mode, which includes energy price shock and disembodied technology shock. The estimation results for SOEs, NSOEs, and FFEs are reported in Table 20.

Table 20: Estimation of structural parameters in extended II model

| Definition for parameters | Parameters | SOEs | NSOEs | FFEs |
|---|---|---|---|---|
| Share of putty-clay investment | $\eta$ | 0.703 | 0.650 | 0.580 |
| | | (0.011) | (0.008) | (0.013) |
| Serial correlation of energy price $P_t^e$ | $\rho_P$ | 0.817 | 0.883 | 0.900 |
| | | (0.008) | (0.004) | (0.007) |
| Serial correlation of disembodied technology $A_t$ | $\rho_A$ | 0.173 | 0.173 | 0.010 |
| | | (0.016) | (0.018) | (0.021) |
| Cross correlation between $P_t^e$ and $A_t$ | $\rho_{PA}$ | 0.150 | 0.050 | 0.050 |
| | | (0.010) | (0.008) | (0.020) |
| Relative standard deviation of innovation to $A_t$ | $\frac{\sigma_A}{\sigma_p+\sigma_A}$ | 0.833 | 0.500 | 0.643 |
| | | (0.023) | (0.001) | (0.007) |
| Objective function in indirect inference | $J(\hat{\psi})$ | 543.763 | 481.786 | 105.157 |

Note: standard errors are in parentheses. The 1% critical value for $J(\hat{\psi})$ is 49.588. Standard errors reported for $\frac{\sigma_A}{\sigma_p+\sigma_A}$ are standard errors of $\sigma_A/\sigma_p$.

To see how the extended model with neutral technologies reproduces the stylized facts, in Tables 21, 22 and 23, we compare the regression results from the estimated model with those from the actual firm-level data for SOEs, NSOEs and FFEs, respectively.

Table 21 compares the coefficients generated by the extended model with the coefficients using the SOEs data. Adding the neutral technology shock into the model, the extended model is able to reproduce the regressions that capture the impact of price changes on energy intensity, however, the extended II model still has difficulty matching the positive coefficients in Regression 3.

Table 21: Comparing extended II model with data for SOEs

| | Model | | | | | SOEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| | | 1-year | 2-year | 3-year | 4-year | | 1-year | 2-year | 3-year | 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P_t^e$ | −0.464 | −0.278 | −0.278 | −0.278 | −0.279 | −0.389 | −0.304 | −0.325 | −0.313 | −0.304 |
| $P_{t-1}^e$ | | −0.233 | −0.138 | −0.141 | −0.137 | | −0.206 | −0.147 | −0.159 | −0.126 |
| $P_{t-2}^e$ | | | −0.117 | −0.046 | −0.050 | | | −0.141 | −0.087 | −0.129 |
| $P_{t-3}^e$ | | | | −0.088 | −0.024 | | | | −0.111 | −0.066 |
| $P_{t-4}^e$ | | | | | −0.079 | | | | | −0.081 |
| Regression 2: Energy intensity responding to the vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P_t^e$ | −0.466 | −0.283 | −0.289 | −0.306 | −0.321 | −0.387 | −0.303 | −0.323 | −0.324 | −0.318 |
| $\frac{NVFA}{OVFA}$ | −0.153 | −0.154 | −0.150 | −0.146 | −0.141 | | −0.125 | −0.108 | −0.148 | −0.128 |
| Lagged $P^e$ | | −0.231 | −0.248 | −0.249 | −0.250 | | −0.205 | −0.285 | −0.339 | −0.379 |
| Regression 3: Vintage structure $NVFA/OVFA$ responding to energy prices | | | | | | | | | | |
| Lagged $P^e$ | −0.014 | −0.014 | −0.011 | −0.006 | −0.001 | 0.012 | 0.013 | 0.031 | 0.040 | 0.059 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "SOEs" are regression results using actual SOEs firm-level data, and these coefficients are also reported in the upper panels of Tables 1, 2 and 3.

For NSOEs, the extended model with disembodied technology shocks can reproduce the stylized facts in all three sets of regressions. Table 22 shows that energy intensity is inelastic with respect to current energy price changes, with significantly negative coefficients for increases in past energy prices. In Regression 1, the coefficients of $NVFA/OVFA$ are now significantly negative, although the magnitudes are slightly larger; and the coefficients in Regression 3 are close to zero, in small magnitude.

Table 22: Comparing extended II model with data for NSOEs

| | Model | | | | | NSOEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| | | 1-year | 2-year | 3-year | 4-year | | 1-year | 2-year | 3-year | 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P_t^e$ | −0.525 | −0.310 | −0.312 | −0.311 | −0.313 | −0.441 | −0.339 | −0.351 | −0.330 | −0.315 |
| $P_{t-1}^e$ | | −0.249 | −0.100 | −0.103 | −0.100 | | −0.217 | −0.121 | −0.119 | −0.074 |
| $P_{t-2}^e$ | | | −0.170 | −0.041 | −0.045 | | | −0.178 | −0.134 | −0.137 |
| $P_{t-3}^e$ | | | | −0.146 | −0.032 | | | | −0.163 | −0.141 |
| $P_{t-4}^e$ | | | | | −0.130 | | | | | −0.048 |
| Regression 2: Energy intensity responding to the vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P_t^e$ | −0.527 | −0.313 | −0.301 | −0.308 | −0.318 | −0.440 | −0.337 | −0.341 | −0.320 | −0.309 |
| $\frac{NVFA}{OVFA}$ | −0.065 | −0.166 | −0.203 | −0.217 | −0.218 | −0.106 | −0.160 | −0.180 | −0.227 | −0.215 |
| Lagged $P^e$ | | −0.252 | −0.287 | −0.299 | −0.306 | | −0.217 | −0.305 | −0.422 | −0.408 |
| Regression 3: Vintage structure $NVFA/OVFA$ responding to energy prices | | | | | | | | | | |
| Lagged $P^e$ | −0.031 | −0.035 | −0.038 | −0.040 | −0.040 | 0.010 | 0 | 0 | 0 | 0 |

Note: the left panel labeled "Model" reports regression coefficients from the estimated model, and right panel labeled "NSOEs" are regression results using actual NSOEs firm-level data, and these coefficients are also reported in the middle panels of Tables 1, 2 and 3. We treat statistically insignificant coefficients as zeros.

Table 23 compares the coefficients generated by the extended II model with coefficients using the data for FFEs. The extended II model is able to reproduce most coefficients from Regression 1, 2, and 3.

Table 23: Comparing extended II model with data for FFEs

| | Model | | | | | FFEs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| | | 1-year | 2-year | 3-year | 4-year | | 1-year | 2-year | 3-year | 4-year |
| Regression 1: Energy intensity responding to energy prices | | | | | | | | | | |
| $P_t^e$ | −0.597 | −0.377 | −0.379 | −0.378 | −0.380 | −0.525 | −0.425 | −0.404 | −0.360 | −0.467 |
| $P_{t-1}^e$ | | −0.250 | −0.096 | −0.099 | −0.096 | | −0.221 | −0.135 | −0.126 | 0 |
| $P_{t-2}^e$ | | | −0.172 | −0.037 | −0.041 | | | −0.155 | −0.095 | 0 |
| $P_{t-3}^e$ | | | | −0.151 | −0.030 | | | | −0.179 | −0.134 |
| $P_{t-4}^e$ | | | | | −0.135 | | | | | −0.089 |
| Regression 2: Energy intensity responding to the vintage structure $NVFA/OVFA$ | | | | | | | | | | |
| $P_t^e$ | −0.595 | −0.379 | −0.366 | −0.371 | −0.380 | −0.525 | −0.425 | −0.401 | −0.349 | −0.415 |
| $\frac{NVFA}{OVFA}$ | 0.073 | 0.033 | 0.020 | 0.016 | 0.018 | 0 | 0 | 0 | 0 | 0 |
| Lagged $P^e$ | | −0.247 | −0.279 | −0.291 | −0.298 | | −0.222 | −0.292 | −0.403 | −0.343 |
| Regression 3: Vintage structure $NVFA/OVFA$ responding to energy prices | | | | | | | | | | |
| Lagged $P^e$ | −0.032 | −0.036 | −0.038 | −0.040 | −0.040 | 0 | 0 | 0 | 0 | 0 |

Note: the left panel labeled “Model” reports regression coefficients from the estimated model, and right panel labeled “Foreign” are regression results using actual foreign firm-level data, and these coefficients are also reported in the lower panels of Tables 1, 2 and 3. We treat statistically insignificant coefficients as zeros.