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Research Article

Determinants of Energy Use in Turkish Manufacturing Industry: A Supply-side View[a]

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This paper aims to assess the supply-side determinants of firm-level energy use. To this end, we first propose a model for a stylized economy using Solovian framework, in which the production function employs energy input, along with capital and labor. We show the full algebraic solution of the model at the steady-state and in the transitional period and derive the supply-side determinants of energy consumption. Then, using firm-level micro panel data on the Turkish manufacturing industry from 2009 to 2015, we test the proposed model with static and dynamic panel data estimators. Our empirical results suggest that the proposed model is consistent with Turkish manufacturing data. Out of the supply-side determinants, firms' output/value-added and total factor productivity, as a proxy for technological progress, are found to be the most significant determinants of firm-level energy use. Estimations also reveal quite heterogenous effects of technology on energy use in different manufacturing subsectors. Hence, although promoting technological change in the manufacturing industry is, without a doubt, the most convenient way to reduce energy use, policymakers should develop sector-specific incentives to achieve this goal.

JEL codes: O41, Q41, L60, C33

Keywords: Solow model, energy use, manufacturing industry, firm-level micro panel data

1 Introduction

Industrial sectors account for the largest share of global energy consumption. According to the International Energy Agency, for instance, 38% of all global final energy use occurred in industry sectors. (IEA, 2021). Moreover, most of the energy input employed in industrial processes still originates from nonrenewable and greenhouse gas (GHG) emitting fossil fuels. Hence, increasing energy efficiency, or decreasing energy intensity measured as energy consumption per unit of output, in industrial sectors remains a key target in global efforts towards mitigating climate change. To develop robust policies, it is essential for policymakers to understand the drivers of energy use in industrial sectors, particularly those with higher energy intensity.

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Since Berndt & Wood (1975) seminal paper, the extensive literature on industrial energy demand has developed in two main streams: (1) on substitution between energy and different factors of production, namely capital and labor, following Griffin & Gregory (1976), and (2) on micro-econometric analysis of energy demand in different industrial sectors, following Woodland (1993). The literature within the second stream that conducts firm- or sectoral-level analyses seems limited and is based on rather small samples. To the authors' best knowledge, out of studies on firm-level analyses, Bjørner et al. (2001) used the largest sample of 2,949 Danish industrial firms over the period from 1983 to 1996. In contrast, Henriksson et al. (2014) and Chaudhry (2016) relied on relatively smaller samples, respectively, of 9 Swedish mining firms over 1990-2005 and 402 Pakistani industrial firms over two years, 2002 and 2006/2007. Agnolucci (2009), moreover, employed sectoral level energy demand data for British and German industrial sectors over the period 1978-2004 and 1991-2004, respectively. Later Agnolucci & De Lipsis (2020) estimated fuel demand across UK industrial subsectors, using aggregated data on eight subsectors between 1990 and 2014. Finally, Su (2018) used data on 32 industrial and service sectors in Taiwan between 1998 and 2015. As expected, all studies reported negative and significant effect of energy prices and technological progress and positive and significant effects of economic activity, namely output or value-added, on industrial energy use.

This article aims to contribute to the above-mentioned stream of literature by proposing and empirically testing a theoretical framework to assess supply-side determinants of energy use. To this end, we first develop a stylized model using the Solovian framework, show the full algebraic solution of the model at the steady-state and in the transitional period, and derive the determinants of energy use. Then, using firm-level micro panel data from the Turkish manufacturing industry, we tested the proposed model empirically.

Our contribution to the literature is two-fold. Firstly, to the best of our knowledge, there exists no similar model, as most studies are based on empirical analyses without providing a theoretical framework. Hence, our study fills an important gap in the literature by proposing a Solovian framework model and algebraically deriving supply-side determinants of energy use. Secondly, as mentioned above, the majority of empirical studies use either aggregated industry or sub-sectoral level data, while only a small minority use firm-level micro panel data with small samples. Moreover, although there exist some Turkish studies on sectoral energy consumption (Oğulata, 2002; Ediger & Huvaz, 2006) and on manufacturing energy consumption (Soytaş & Sarı, 2007; Önüt & Soner, 2007; Bölük & Koç, 2010; Akyürek, 2020), all of these use aggregated data.[1] We, on the other hand, provide empirical evidence using a large unbalanced micro panel data set of 29,892 Turkish manufacturing firms over the period from 2009 to 2015. Our analyses would also provide significant policy implications because our dataset allows us to conduct the estimations for 24 manufacturing subsectors and, hence, to identify sub-sectoral heterogeneity.

Three main results are achieved in this paper. (1) Both steady-state and transitional dynamics solution of the proposed stylized model leads to an equation representing supply-side determinants of per labor energy consumption. All the variables derived from the equation are found to be consistent with the literature. (2) Empirical estimations suggest

[1] Authors are aware of only one unpublished study employing firm-level data on Turkish manufacturing industry, namely Şahin (2017). Yet, the main objective of that study is to decompose manufacturing energy consumption rather than deriving determinants of energy use.

that the equation on supply-side determinants of energy use, developed within the proposed stylized model, is found to be consistent with the Turkish manufacturing data. Results suggest, in accordance with the previous literature, that while economic activity has a positive and significant effect on firm-level energy use, technological progress, proxied by total factor productivity, has a significantly negative effect. (3) Empirical results on Turkish manufacturing sub-sectors suggest, moreover, that although technological progress has a negative and significant effect in most subsectors, the effect is quite heterogenous depending on the energy intensity structure, such that the estimated effect is smaller (larger) in more (less) energy-intense sectors.

The current paper is structured as follows. In Section 2, the proposed model is described, and a full algebraic solution of the model is provided. Section 3 is devoted to the empirical analysis, namely data and methodology. In Section 4, empirical results, along with discussions, are provided. Finally, Section 5 concludes with policy implications.

2 Model

Consider a stylized economy with the following Cobb-Douglas production technology:[2]

$$Y_t = K_t^{\alpha} R_t^{\beta} (A_t\ L_t)^{(1-\alpha-\beta)} \tag{1}$$

where the final good Y_t is produced using physical capital K_t, energy resource R_t and efficient labor $A_t\ L_t$. In equation (1), α and β represent the output elasticities of physical capital and energy, respectively, and the dynamics of labor force and technological progress are $L_t = L_0\ e^{nt}$ and $A_t = A_0\ e^{xt}$, where L_0 and A_0 are initial values and n and x are exogenous growth rates of technology and labor, respectively.

Assumption 1: Energy resource expenditure in the economy is financed via the saving of output/income generated: $R_t = s_R\ Y_t$, where s_R is the saving rate for energy resource expenditure.[3]

Assumption 1 under closed economy without government will lead to following macroeconomic equilibrium:[4]

$$Y_t - R_t = C_t + I_t \tag{2}$$

where C_t is the consumption of final good, I_t is the gross investment with the form $\dot{K}_t + \delta K_t$. Noting that $Y_t - C_t = S_t$, equation (2) can be re-written as:

$$S_t = sY_t = \dot{K}_t + \delta K_t + s_R Y_t \tag{3}$$

where s represents the composite saving rate with two components, namely saving rate for energy resource expenditure (s_R) and saving rate for physical capital accumulation (s_K); $s = s_R + s_K$.

[2] The Cobb-Douglas form ensures that all factors of production are essential. Moreover, the homogeneity of degree one assumption of the production function guarantees that the real profit is zero, a salient feature of perfectly competitive markets.

[3] We also implicitly assume that the economy under consideration is small, with relatively small demand of energy resource; hence there exists an infinite stock of resource available.

[4] Although this formulation of market clearing condition of final output is derived from Assumption 1, it highly resembles that of proposed by Acemoğlu et al. (2012, equation 8 on p. 136).

Equations (1) and (3) together imply the following capital accumulation function for the stylized economy:

$$\dot{K}_t = s_K K_t^{\alpha} R_t^{\beta} (A_t \; L_t)^{(1-\alpha-\beta)} - \delta K_t \tag{4}$$

Capital accumulation function in (4) can be re-expressed in per efficient capita as follows:

$$\dot{\tilde{k}}_t = s_K \tilde{y}_t - (n+\delta+x)\tilde{k}_t \tag{5}$$

where $\tilde{k}_t = \frac{K_t}{A_t \; L_t}$, $\tilde{r}_t = \frac{R_t}{A_t \; L_t}$, $\tilde{y}_t = \frac{Y_t}{A_t \; L_t}$, and hence, $\tilde{y}_t = \tilde{k}_t^{\alpha} \; \tilde{r}_t^{\beta}$. Moreover, using Assumption 1 in the production function leads to $\tilde{y}_t = \tilde{k}_t^{\alpha/(1-\beta)} \; s_R^{\beta/(1-\beta)}$ and hence equation (5) can be re-written as:

$$\dot{\tilde{k}}_t = s_K \tilde{k}_t^{\alpha/(1-\beta)} \; s_R^{\beta/(1-\beta)} - (n+\delta+x)\tilde{k}_t \tag{6}$$

The standard steady-state (ss) solution procedure of this model will lead to:

$$\tilde{k}_{ss} = \left(\frac{s_K}{(n+\delta+x)}\right)^{(1-\beta)/(1-\alpha-\beta)} \qquad s_R^{\beta/(1-\alpha-\beta)} \tag{7a}$$

$$\tilde{y}_{ss} = \left(\frac{s_K}{(n+\delta+x)}\right)^{\alpha/(1-\alpha-\beta)} \qquad s_R^{\beta/(1-\alpha-\beta)} \tag{7b}$$

$$\tilde{r}_{ss} = \left(\frac{s_K}{(n+\delta+x)}\right)^{\alpha/(1-\alpha-\beta)} \qquad s_R^{(1-\alpha)/(1-\alpha-\beta)} \tag{7c}$$

Noting that $\tilde{r}_{ss} = R_{ss}/(A_t \; L_t)$ and that $A_t = A_0 \; e^{xt}$, taking natural logarithm of equation (7c) will lead to

$$lnr_{ss} = lnA_0 + xt + \left(\frac{\alpha}{1-\alpha-\beta}\right) lns_K - \left(\frac{\alpha}{1-\alpha-\beta}\right) ln(n+\delta+x) + \left(\frac{1-\alpha}{1-\alpha-\beta}\right) lns_R \tag{8}$$

Moreover, the standard transitional period solution of the model will lead to the path of $\tilde{r}_t$:

$$\tilde{r}_t = \left[\frac{s_K \; s_R^{(1-\alpha)/\alpha}}{(n+\delta+x)} + const \; e^{-(n+\delta+x) \; \frac{(1-\alpha-\beta)}{\alpha} \; t}\right]^{\alpha/(1-\alpha-\beta)} \tag{9}$$

Log-linearization and Taylor series approximation of (9) leads to the following convergence equation for $\tilde{r}_t$:

$$\begin{aligned} ln\tilde{r}_{t_2} = e^{-v\tau} \; lnr_{t_1} + \left(\frac{\alpha}{1-\alpha-\beta}\right)[1-e^{-v\tau}] \; lns_K + \left(\frac{1-\alpha}{1-\alpha-\beta}\right)[1-e^{-v\tau}] \; lns_R \\ - \left(\frac{\alpha}{1-\alpha-\beta}\right)[1-e^{-v\tau}] \; ln(n+\delta+x) \end{aligned}$$

or for $r_t = R_t/L_t$, the above equation could be re-written as:

$$\begin{aligned} lnr_{t_2} = e^{-v\tau}\ ln\tilde{r}_{t_1} + \left(\frac{\alpha}{1-\alpha-\beta}\right)[1-e^{-v\tau}]\ lns_K + \left(\frac{1-\alpha}{1-\alpha-\beta}\right)[1-e^{-v\tau}]\ lns_R \\ - \left(\frac{\alpha}{1-\alpha-\beta}\right)[1-e^{-v\tau}]\ ln(n+\delta+x) + [1-e^{-vt}]\ lnA_0 + x(t_2 - t_1\ e^{-vt}) \end{aligned} \tag{10}$$

where $v = (1-\alpha-\beta)/(1-\beta)\ (n+\delta+x)$ and $\tau = t_2 - t_1$.

3 Empirical Analyses

Equations (8) and (10) derived in Section 2 will be used to empirically analyze supply-side determinants of firm-level energy use in the Turkish manufacturing industry. The model depicted in Section 2 is convenient for Turkish manufacturing data as, according to Turkey's Ministry of Energy and Natural Resources statistics (MENR, 2022), industrial sectors with more than a one-third share in the country's primary energy consumption are the largest consumers of energy. Moreover, considering the firm-level characteristics of the data set described in Section 3.1, an individual manufacturing firm's energy input is financed through the value of output generated by the firm. This is consistent with the Assumption 1 in Section 2.

3.1 Data

We use a firm-level panel dataset compiled from Annual Statistics on Industry and Services provided by the Turkish Statistical Institute (TURKSTAT), involving unbalanced panel data of 128,813 manufacturing firms over the 7 years between 2009 and 2015. The data set provides various firm-level characteristics, including the number of employees, expenditures on inputs, tangible and intangible investments, depreciation allowances, the value of output and value-added generated. We first generated firm-level energy input (R_{it}) variable using the energy expenditure data and real price index series provided by the International Energy Agency (IEA) Energy Prices and Taxes database.[5] Moreover, as both equation (8) and equation (10) require technological progress variable, we calculate total factor productivity (TFP) for each firm following Olley & Pakes (1996):[6]

$$lnY_{it} = \beta_0 + \beta_1 lnK_{it} + \beta_2 lnL_{it} + \beta_3 R_{it} + \beta_4 lnM_{it} + \beta_5 a_{it} + u_{it}$$

where $Y_{it}, K_{it}, L_{it}, R_{it}$ and M_{it} represent output, capital stock, labor, energy input and material input of firm i in year t, respectively and a_{it} is the age of the firm. The composite error term u_{it} is further described as:

$$u_{it} = \Omega_{it} + \eta_{it}$$

[5] All nominal monetary values are converted to real values using the Turkish Statistical Institute Domestic Producer Price Index deflator data (2003=100) on the basis of manufacturing subsectors See: `https://data.tuik.gov.tr/Bulten/Index?p=Yurt-Ici-Uretici-Fiyat-Endeksi-Aralik-2021-45849`. Last access date: 15.04.2022.

[6] The authors are aware that there are numerous methods (parametric, semi-parametric and non-parametric) to estimate firm-level total factor productivity. Yet, as the main objective of this research is to assess the effects of various supply-side factors on firm-level energy use, we use this relatively simple method proposed by Olley & Pakes (1996).

where Ω_{it} captures the total factor productivity of firm i in year t, and η_{it} includes all other uncontrollable factors (Yaşar et al., 2008). Since our data set provides no information on existing capital stock for each firm, following Kılıçaslan et al. (2017), we employed the following Perpetual Inventory Method (PIM) to generate firm-level capital stock series:

$$K_{i,t} = K_{i,t-1} + I_{i,t} - \delta K_{i,t-1}$$

where $I_{i,t}$ represents investment in tangible assets of firm i in year t, and δ is the rate of depreciation of capital stock.[7]

The calculations described above obtained an unbalanced firm-level micro panel data set involving data of 29,892 manufacturing firms over the years between 2009 and 2015.[8] The firms in the data set operate in 24 different manufacturing subsectors according to NACE Rev.2 classification.[9] The largest sectors in terms of annual average number of firms are "14. Manufacture of clothing", "13. Manufacture of textile products", "25. Manufacturing of fabricated metal products (excluding machinery and equipment)", and the smallest are "12. Manufacture of tobacco products", "19. Manufacture of coke and refined petroleum products" and "11. Manufacture of beverages". In addition to the NACE Rev.2 classification, firms are also classified by technology[10] and size.[11] According to technology classification, approximately 49% of 29,892 companies in all years are in low technology sectors (tech=1), 27.5% in medium-low technology sectors (tech=2), and 21.5%, in medium-high technology sectors. (tech=3) and only 2%, in high-tech sectors (tech=4). According to the size classification, about 4.5% of all companies are micro enterprises (size=1), 47% are small enterprises (size=2), 38% are medium-sized (size=3), and 10.5% are large enterprises (size=4). The basic descriptive statistics of the key variables in the data set are given in Table 1.[12]

Table 1: Descriptive statistics of natural logarithms of key variables

Variable	# of Observations	Mean	Std. Dev.	Min.	Max.
lnY	3,763	12.44	1.05	9.34	17.37
lnL	3,763	1.34	0.53	0.69	2.20
lnM	3,763	11.93	1.18	2.60	16.68
lnR	3,763	3.84	1.12	-5.70	9.18
lnK	3,763	10.95	1.44	3.78	16.92
lnVA	3,763	10.66	1.09	3.94	16.00
lnTFP	3,763	1.48	0.10	-1.05	2.20

Notes: VA and tfp represent value-added and total factor productivity, respectively.

[7] We assumed constant annual depreciation rate of 7.5% and used depreciation allowances to calculate initial capital stock $K_{i,0}$ following Kılıçaslan et al. (2017).

[8] Due to the unavailability of investment data for most of the firms, we lost many observations during the capital stock calculation.

[9] `https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF`. Last access date: 18.04.2022.

[10] `https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf`. Last access date: 18.04.2022

[11] `https://data.oecd.org/entrepreneur/enterprises-by-business-size.htm`. Last access date: 18.04.2022

[12] One of the most frequently encountered issues in these types of micro panel data sets is the existence of outliers. We observed that taking natural logarithm of the variables overcomes the issue of outliers.

3.2 Methodology

Rewriting equation (8) for empirical purposes will lead:

$$lnr_{it} = \alpha + \beta_1 lns_{K,it} + \beta_2 lns_{R,it} + \beta_3 ln(n_{it} + \delta + x_{it}) + \beta_4 lnA_{0,it} + \beta_5 x_{it} + \mu_i + \epsilon_{it} \quad (11)$$

where i and t represent the cross-section (29,892 firms) and time (7 years between 2009 and 2015) dimension of the panel dataset, and r is per labor energy input of the firm. Moreover, n, δ, x and A_0 represent labor growth rate, capital stock depreciation rate (assumed to be constant at 7.5%), total factor productivity (TFV) growth rate and initial level of total factor productivity of the firm, respectively, and μ_i and ϵ_{it} are individual fixed effects and the idiosyncratic error term, respectively. Finally, s_R and s_K, which are respectively defined in Section 2 as saving rate for energy resource expenditure and saving rate for physical capital accumulation, can be further defined as energy input to output ratio, i.e., energy intensity, and capital to output ratio considering the structure of the data set used. Hence, lns_R and lns_K could further be re-written as $lns_R = lnr - lny$ and $lns_K = lnk - lny$, respectively. The equation (11) would then be reformulated as:

$$lnr_{it} = \alpha + \beta_1 lnk_{it} + \beta_2 lny_{it} + \beta_3 ln(n_{it} + \delta + x_{it}) + \beta_4 lnA_{0,it} + \beta_5 x_{it} + \mu_i + \epsilon_{it} \quad (12)$$

where k and y represent per worker capital stock and per worker output, respectively.[13]

Equation (12) would be estimated using Fixed Effects (FE) and Random Effects (RE) estimators for both the manufacturing industry as a whole and for different company groups. However, it is frequently suggested in the empirical literature that there exists evidence pointing towards persistency in energy consumption (e.g., Narayan & Smyth (2007); Smyth (2013); Bozoklu et al. (2020)). Such persistence requires dynamic modeling of firm-level energy use. Equation (10), derived in Section 2, will be used to estimate this dynamic nature. Rewriting equation (10) for empirical purposes will lead to:

$$lnr_{it} = \alpha + \beta_1 lnr_{it-1} + \beta_2 lnk_{it} + \beta_3 lny_{it} + \beta_4 ln(n_{it} + \delta + x_{it}) + \beta_5 lnA_{0,it} + \beta_6 x_{it} + \mu_i + \epsilon_{it} \quad (13)$$

Dynamic panel data model depicted in equation (13) will be estimated using the Difference GMM estimator proposed by Arellano & Bond (1991) and System GMM estimator proposed by Arellano & Bond (1995) and Blundell & Bond (1998, 2000). Although both equation (12) and equation (13) are directly derived from the model developed in Section 2, all independent variables included are in accordance with the previous literature. The main independent variable used in almost all the empirical studies on modeling the energy demand of industrial firms is either production/output (Henriksson et al., 2014; Chaudhry, 2016; Gutiérrez-Pedrero et al., 2018) or value-added (Bjørner et al., 2001; Su, 2018). Both variables are expected to have a positive effect on energy demand. Another key variable added to estimations in the literature is the energy price (Bjørner et al., 2001; Henriksson et al., 2014; Su, 2018). Yet, as stated above, there is no firm-level energy price variable in the data set on an individual firm basis, and the energy input is, in fact, calculated using a real energy price index. Among other variables, capital stock is also one of the most

[13] In empirical estimations, we use both per worker output (Model 1) and per worker value-added (Model 2) for the sake of completeness.

frequently used explanatory variables in the literature (Gutiérrez-Pedrero et al., 2018). The expected effect of capital stock depends on whether it is a substitute or complementary to energy input. Finally, due to the fact that technological development will increase energy efficiency and hence decrease energy consumption, total factor productivity has been used as an indicator of technological development (Henriksson et al., 2014).

4 Results and Discussion

Table 2 presents the results of the estimation of equation (12) using output (Model 1) and value-added (Model 2) as main independent variables with Pooled OLS (POLS), Fixed Effects (FE) and Random Effects (RE) estimators. As expected, both the output ($\boldsymbol{lny}$) and the value-added ($\boldsymbol{lnva}$) of the firm affect energy consumption positively and significantly. According to the FE estimation results, output and value-added elasticity of energy consumption are 0.490 and 0.126, respectively.[14] Estimations also reveal, in accordance with expectations, that TFP growth rate ($\boldsymbol{lnx}$) affects energy consumption negatively and significantly, such that a 1% increase in TFP of the firm decreases energy consumption by 0.659% and 0.369% in Model 1 and Model 2, respectively. Finally, we find that the capital stock variable ($\boldsymbol{lnk}$) has a positive and statistically significant effect, while as expected $\boldsymbol{ln(n+\delta+x)}$ has a negative and statistically significant effect on energy consumption.

Table 2: Estimation of equation (12) using different estimators for the whole panel dataset

Dependent Variable: $\boldsymbol{lnr}$	**Model 1** POLS	FE	RE	**Model 2** POLS	FE	RE
$\boldsymbol{constant}$	-3.062***	-0.616***	-2.480***	-2.424***	2.916***	-1.359***
	(0.099)	(0.199)	(0.166)	(0.098)	(0.139)	(0.170)
$\boldsymbol{lny}$	0.445***	0.386***	0.490***			
	(0.008)	(0.014)	(0.010)			
$\boldsymbol{lnva}$				0.177***	0.126***	0.189***
				(0.010)	(0.009)	(0.009)
$\boldsymbol{lnk}$	0.255***	0.028***	0.107***	0.332***	0.038***	0.144***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
$\boldsymbol{x}$	-0.905***	-0.659***	-0.736***	-0.332***	-0.369***	-0.325***
	(0.080)	(0.058)	(0.057)	(0.078)	(0.054)	(0.052)
$\boldsymbol{ln(n+\delta+x)}$	0.101***	-0.257***	0.042***	0.088***	-0.365***	0.001
	(0.004)	(0.016)	(0.007)	(0.004)	(0.017)	(0.008)
$\boldsymbol{lnA_0}$	-1.318***	NA	-0.926***	-0.020	NA	0.633***
	(0.075)	NA	(0.116)	(0.075)	NA	(0.118)
# of observations	52,469	52,469	52,469	52,469	52,469	52,469
F/Wald Statistics	1,409.29***	4,631.91***	212.48***	928.07***	2,127.58***	124.82***
Robust Hausman χ^2 Stat.			1,069.94***			844.97***

Notes: *, ** and *** indicate 10%, 5% and 1% significance level, respectively. A full set of time dummies is included in all estimations. Robust standard errors are given in parentheses. Robust Hausman test is employed with the bootstrap method with 100 repetitions. In addition, the reason for the decrease in the number of observations is the loss of one-year data while calculating the TFP growth rate, and the reason for the decrease in the number of firms is the lack of TFP and value-added data in some companies.

[14] Robust Hausman Chi-square statistics are given under the RE estimator columns in the table. According to Hausman tests, the RE estimator gives biased estimates. Besides, POLS estimator results are given for comparison purposes only. Therefore, only the FE estimator results are discussed in the text.

The results reported in Table 2 show that the equation derived via the Solow framework can be verified using the whole panel of Turkish manufacturing firms. Estimating the equation (12) for different groups of firms would not only provide more evidence towards the validity of the proposed model but also shed more light on the dynamics of firm-level energy use in the Turkish manufacturing industry. To this end, estimation results for 24 manufacturing subsectors according to NACE classification are presented in Table 3.[15] Similar to the results for the whole panel, Table 3 shows that the effect of the output on energy consumption is positive and statistically significant in every sector, except for "19. Manufacture of coke and refined petroleum products". The largest output elasticity of energy consumption is recorded in subsectors "17. Manufacture of paper and paper products", "22. Manufacture of rubber and plastic products", and "20. Manufacture of chemicals and chemical products".

Moreover, estimations reveal that the effect of TFP growth rate on energy consumption is quite heterogenous in manufacturing subsectors. Although in most subsectors, i.e., 16 out of 24, we find a negative and significant effect, the magnitude differs substantially. While the largest and most significant effects are, respectively, recorded in subsectors "31. Manufacture of furniture", "22. Manufacture of rubber and plastic products", "24. Manufacture of basic metals", the effect is insignificant in eight subsectors, including "11. Manufacture of beverages", "12. Manufacture of tobacco products" and "23. Manufacture of other non-metallic mineral products". This finding is particularly interesting since, in our panel, subsector "23. Manufacture of other non-metallic mineral products" is the most energy-intensive sector, while "31. Manufacture of furniture" is among those with the lowest energy-intensity.[16] Hence, technological progress, proxied by total factor productivity growth rate, seems to have limited effect on manufacturing subsectors, whose production by nature is energy intensive.

[15] For the sake of space, we only provide estimation results of Model 1 hereafter. Results of Model 2 are provided in the Appendix.
[16] Please see https://www.eia.gov/outlooks/ieo/pdf/industrial.pdf. Last access date: 22.06.2022

Table 3: Fixed Effects estimation results of equation (12) for different manufacturing subsectors (NACE): Model 1

Dependent Variable: *lnr*	10	11	12	13	14	15	16	17	18	19	20	21
constant	-0.618	0.337	16.400*	-0.490	-0.359	1.934***	-0.125	-1.546	-0.734	0.851	-0.673	0.168
	(0.687)	(2.275)	(9.173)	(0.610)	(0.390)	(0.712)	(2.008)	(1.599)	(1.143)	(4.028)	(1.567)	(2.561)
lny	0.411***	0.409***	-0.744	0.396***	0.317***	0.204***	0.359**	0.485***	0.342***	0.423	0.453***	0.378**
	(0.049)	(0.137)	(0.772)	(0.041)	(0.027)	(0.050)	(0.143)	(0.118)	(0.093)	(0.334)	(0.098)	(0.152)
lnk	0.035*	-0.018	0.240	0.022*	0.032**	-0.002	0.055	0.046	0.004	0.006	-0.041	0.065
	(0.018)	(0.054)	(0.302)	(0.012)	(0.015)	(0.026)	(0.034)	(0.028)	(0.019)	(0.132)	(0.028)	(0.066)
$\boldsymbol{x}$	-1.137***	0.247	2.591	-0.619***	-0.328***	-0.620**	-0.132	-0.954***	-0.613*	-2.514*	-1.086***	-0.580*
	(0.237)	(0.236)	(2.030)	(0.135)	(0.112)	(0.249)	(0.470)	(0.357)	(0.348)	(1.484)	(0.347)	(0.315)
$\boldsymbol{ln(n+\delta+x)}$	-0.282***	-0.308*	-1.184**	-0.172***	-0.269***	-0.422***	-0.298**	-0.326***	-0.088	-0.846***	-0.258**	-0.328*
	(0.046)	(0.176)	(0.515)	(0.055)	(0.033)	(0.064)	(0.151)	(0.094)	(0.145)	(0.266)	(0.121)	(0.173)
# of observations	4,954	398	66	6,255	6,914	1,167	653	1,528	843	155	1,812	472
F/Wald Statistics	32.16***	4.56***	5.32***	34.58***	56.64***	12.10***	6.05***	9.97***	4.30***	5.36***	11.91***	7.55***
	22	23	24	25	26	27	28	29	30	31	32	33
constant	-0.807	-1.548	-0.677	0.451	2.525*	-0.068	0.636	-0.451	0.098	-0.850	1.669*	-2.426
	(0.707)	(1.087)	(1.193)	(0.541)	(1.385)	(1.144)	(0.644)	(0.818)	(2.617)	(0.788)	(0.932)	(2.047)
lny	0.473***	0.534***	0.429***	0.311***	0.188**	0.336***	0.246***	0.365***	0.344**	0.411***	0.109*	0.287***
	(0.055)	(0.079)	(0.083)	(0.042)	(0.086)	(0.076)	(0.045)	(0.060)	(0.140)	(0.060)	(0.064)	(0.090)
lnk	0.028	0.025	0.035	-0.002	0.026	0.026	0.034*	0.008	-0.074	0.012	0.006	0.239*
	(0.019)	(0.0322)	(0.025)	(0.014)	(0.029)	(0.020)	(0.018)	(0.022)	(0.185)	(0.019)	(0.037)	(0.123)
$\boldsymbol{x}$	-1.231***	-0.141	-1.173***	-0.554***	-0.153	-0.536*	-1.005***	-0.492**	-0.789	-1.464***	-0.206	-0.657
	(0.429)	(0.196)	(0.399)	(0.182)	(0.373)	(0.282)	(0.199)	(0.206)	(0.521)	(0.283)	(0.172)	(0.524)
$\boldsymbol{ln(n+\delta+x)}$	-0.349***	-0.204**	-0.257***	-0.312***	-0.524***	-0.340***	-0.336***	-0.203***	-0.096	-0.344***	-0.131	-0.214
	(0.041)	(0.081)	(0.091)	(0.045)	(0.107)	(0.100)	(0.058)	(0.072)	(0.176)	(0.068)	(0.110)	(0.186)
# of observations	4,028	3,423	1,996	5,138	637	2,490	4,617	2,424	494	2,100	1,249	358
F/Wald Statistics	51.03***	11.08***	9.05***	19.99***	8.89***	14.70***	19.94***	14.48***	2.51**	16.58***	7.84***	5.28***

Notes: *, ** and *** indicate 10%, 5% and 1% significance level, respectively. A full set of time dummies is included in all estimations. Robust standard errors are given in parentheses.

Table 4 shows estimation results for different firm groups by technology level and size. Estimated parameters for output elasticity of energy consumption are positive and significant, and those for TFP are negative and significant for all groups except for micro-sized enterprises (size=1). Similar to the discussions above, the magnitude of the effect of the TFP variable on different firm groups is heterogenous, with the highest being for firms in the medium-high technology level (tech=3) group.

Table 4: Fixed Effects estimation results of equation (12) for firm groups by technology and size: Model 1

Dependent Variable: lnr	**Technology**				**Size**			
	Tech=1	Tech=2	Tech=3	Tech=4	Size=1	Size=2	Size=3	Size=4
$constant$	-0.367	-0.609	-0.132	1.621	-2.297	-0.289	-0.238	-0.311
	(0.248)	(0.410)	(0.480)	(1.177)	(2.557)	(0.288)	(0.320)	(0.748)
lny	0.351***	0.425***	0.337***	0.265***	0.144	0.337***	0.368***	0.421***
	(0.018)	(0.030)	(0.034)	(0.072)	(0.185)	(0.021)	(0.022)	(0.050)
lnk	0.034***	0.024**	0.009	0.047	0.378***	0.026***	0.028***	0.018
	(0.007)	(0.011)	(0.014)	(0.030)	(0.128)	(0.008)	(0.009)	(0.017)
x	-0.576***	-0.626***	-0.835***	-0.392*	-0.062	-0.651***	-0.602***	-0.632***
	(0.069)	(0.126)	(0.151)	(0.223)	(0.562)	(0.086)	(0.081)	(0.241)
$ln(n+\delta+x)$	-0.242***	-0.290***	-0.268***	-0.451***	-0.255	-0.280***	-0.286***	-0.233***
	(0.021)	(0.031)	(0.039)	(0.094)	(0.320)	(0.035)	(0.024)	(0.052)
# of observations	26,127	15,098	11,837	1,109	264	21,725	24,684	7,498
# of firms	7,704	4,495	3,516	330	185	8,584	7,970	2,003
F/Wald Statistics	115.39***	61.52***	38.26***	11.49***	4.86***	50.83***	84.06***	31.31***

Notes: *, ** and *** indicate 10%, 5% and 1% significance level, respectively. A full set of time dummies is included in all estimations. Robust standard errors are given in parentheses.

GMM estimation results of equation (13) with both one-step (one-step) and two-step (two-step) Difference and System GMM methods are provided in Table 5.[17] Our micro-panel data is suitable for GMM approaches, which are generally designed for panels with short time and large cross-sectional dimensions (Roodman, 2009a). Moreover, as a rule of thumb, GMM estimators require the number of groups to be larger than the number of instruments (Roodman, 2009b), which is not an issue in micro-panels such as ours. The results of the other post-estimation tests, namely Hansen J-test (Hansen, 1982), Difference-in-Hansen test (Blundell & Bond, 1998) and second- or third-order serial correlation tests (Arellano & Bond, 1991) are provided in the lower panel of the table.

Results shown in Table 5 suggest that the coefficient of lnr_{t-1} is negative and statistically significant in the Difference GMM estimation. This result is quite surprising because it would not be expected that the previous year's energy consumption would decrease a firm's current energy consumption. This result, along with the Hansen J-test rejecting the null hypothesis at a 10% significance level, brings into question the reliability of the Difference GMM estimation. In addition, it is seen that the coefficient of lnr_{t-1} is positive and statistically significant, as expected in the System GMM estimation. However, in the Difference GMM estimation, the coefficient of the output lny is positive and insignificant, whereas in the System GMM estimation, contrary to expectations, it is negative and significant. The only possible explanation is that the dependent variable lnr is mainly explained by its first lag, lnr_{t-1}. The fact that the coefficient of lnr_{t-1} is very close to 1, especially the two-stage system GMM estimation, suggests that the energy consumption series in our dataset

[17] In all of these estimations, Model 1, namely output as the main independent variable, is considered.

Table 5: Estimating equation (13) with GMM methods

Dependent Variable $\boldsymbol{lnr}$	**Difference GMM One Step**	**Difference GMM Two Step**	**System GMM One Step**	**System GMM Two Step**
$\boldsymbol{lnr_{t-1}}$	-0.075**	-0.080**	0.878***	0.905***
	(0.035)	(0.035)	(0.125)	(0.110)
$\boldsymbol{lny}$	0.073	0.056	-0.220**	-0.204**
	(0.086)	(0.085)	(0.095)	(0.079)
$\boldsymbol{lnk}$	-0.046***	-0.049***	0.038	0.035
	(0.015)	(0.014)	(0.025)	(0.023)
$\boldsymbol{x}$	-0.386***	-0.343***	-0.971***	-0.887***
	(0.091)	(0.088)	(0.343)	(0.305)
$\boldsymbol{ln(n+\delta+x)}$	-0.783***	-0.793***	-0.001	0.009
	(0.169)	(0.165)	(0.020)	(0.018)
# of observations	25,648	25,648	37,757	37,757
# of Firms (Groups)	9,369	9,369	11,998	11,998
# of Instruments	27	27	30	30
Wald statistics	221.41***	217.13***	439.39***	438.42***
AR(2) test z- statistics	-1.53	-1.65	3.48	4.22
	(0.126)	(0.100)	(0.000)	(0.000)
AR(3) test z- statistics			-0.25	-0.25
			(0.800)	(0.805)
Hansen J-test	26.21	26.21	24.91	24.91
	(0.095)	(0.095)	(0.205)	(0.205)
Difference-in-Hansen test	7.21	7.21	3.24	3.24
	(0.125)	(0.125)	(0.518)	(0.518)

Notes: *, ** and *** indicate 10%, 5% and 1% significance level, respectively. A full set of time dummies is included in all estimations. Robust standard errors are given in parentheses for the estimated coefficients. Probability values (p-values) are given in parentheses for AR(2), AR(3), Hansen J- and Difference-in-Hansen tests. When the result of the AR(2) test showed that the serial correlation problem was not solved, estimations carried out with deeper lag lengths, hence in these cases, the AR(3) test statistics are also provided. Number of firms decline significantly due to the unavailability of lagged energy consumption data for many firms.

is highly persistent, as suggested by previous literature (Narayan & Smyth, 2007; Smyth, 2013). Another issue that emerged in the system GMM estimations is that the coefficients of the $\boldsymbol{lnk}$ and $\boldsymbol{(n+\delta+x)}$ variables are statistically insignificant, but the effect of the TFP growth rate variable (x) is negative and highly significant, similar to the findings in the FE estimation of equation (12).

5 Conclusions and Policy Implications

In this paper, we proposed a model for a stylized economy in which energy resource, along with capital and labor, is a factor of production. Full algebraic solution of the model at the steady-state and in the transitional period led us to identify the supply-side determinants of energy consumption. Then, we used firm-level micro panel data on Turkey's manufacturing industry to test the proposed model empirically.

When all empirical results are considered together, the model we propose is found to be consistent with the data. Particularly, Fixed Effects estimation results on the whole panel suggest that all key variables proposed by the model are statistically significant. Moreover, we found, in accordance with the previous empirical literature, that while firms' output and value-added positively affect firm-level energy use, technological progress proxied by total factor productivity has a negative effect. We also tested the proposed model using data on different firm groups classified by manufacturing subsectors, technology level and size. Results, achieved especially for manufacturing subsectors, are of significant importance for policymakers since, despite a negative effect for total factor productivity variable in almost all subsectors, the effect is quite heterogenous. In fact, we found that in sectors with high energy intensity, technological progress has only limited effect in decreasing energy use. Hence, although our model and empirical results point out that promoting technological progress is an effective way to reduce manufacturing energy consumption, and therefore policymakers should focus on designing subsector-specific policies accordingly.

This finding is particularly important for policymakers in Turkey, which has a relatively long history of endeavor towards decreasing energy consumption via promoting energy efficiency due its heavy reliance on imported energy.[18] Industrial sectors are the largest contributors to energy consumption, and attempts are made to increase energy efficiency and, hence, decrease energy consumption in these sectors. For instance, the goal of "reducing energy intensity in each industrial sub-sector by not less than 10%" was emphasized in both 2012 Energy Efficiency Strategy Document (MENR, 2012), which covers the period between 2012 and 2023 and the 2017 National Energy Efficiency Action Plan (MENR, 2017), which covers the period between 2017 and 2023, Yet, when total energy intensity of industry is considered, these targets seem inadequate in achieving an energy-efficient industry. The period between 2003 and 2012 saw industrial energy intensity decline almost 50%, but from 2013 until 2020, it showed a slight increase (MENR, 2022; TURKSTAT, 2021). Hence, a new perspective is needed which specifies heterogenous targets for individual industrial sectors. Our findings suggest that policymakers should differentiate these targets considering the energy intensity dynamics of each subsector. Bearing in mind that fossil fuels still constitute the largest share in Turkey's primary energy consumption and that EU countries account for more than 42% of Turkey's total exports (TURKSTAT, 2021), achieving larger declines in energy consumption would further help the country to mitigate the adverse effects of the upcoming Carbon Border Adjustment Mechanism proposed within the framework of European Green Deal's "Fit for 55" package (EC, 2021).

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[18] Turkey's primary energy import dependency was 77.5% in 2020 (MENR, 2022).

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Appendix

Table A.1: Fixed Effects estimation results of equation (12) for different manufacturing subsectors (NACE): Model 2

Dependent Variable: ln r	10	11	12	13	14	15	16	17	18	19	20	21
constant	3.691***	3.681**	9.405*	3.497***	1.956***	3.513***	3.938***	3.644***	2.268**	4.303**	4.560***	3.955***
	(0.352)	(1.433)	(4.405)	(0.378)	(0.356)	(0.778)	(1.132)	(0.654)	(1.064)	(1.865)	(0.945)	(1.386)
lnva	0.102***	0.202***	-0.227	0.100***	0.156***	0.087	0.067	0.101**	0.119	0.183	0.097*	0.158***
	(0.022)	(0.070)	(0.213)	(0.027)	(0.027)	(0.085)	(0.084)	(0.044)	(0.117)	(0.171)	(0.056)	(0.051)
lnk	0.042**	-0.026	0.169	0.033**	0.043***	0.000	0.077**	0.067**	0.004	0.008	-0.034	0.061
	(0.019)	(0.057)	(0.217)	(0.013)	(0.015)	(0.030)	(0.035)	(0.027)	(0.021)	(0.139)	(0.029)	(0.064)
$\boldsymbol{x}$	-0.739***	0.104	1.817	-0.358***	-0.160	-0.370	0.329	-0.595**	-0.433	-1.709*	-0.816**	-0.366
	(0.226)	(0.218)	(1.331)	(0.139)	(0.109)	(0.272)	(0.375)	(0.299)	(0.336)	(0.979)	(0.330)	(0.245)
$\boldsymbol{ln(n+\delta+x)}$	-0.415***	-0.445**	-1.020**	-0.301***	-0.354***	-0.457***	-0.498***	-0.508***	-0.163	-0.878***	-0.465***	-0.501***
	(0.046)	(0.175)	(0.450)	(0.056)	(0.037)	(0.063)	(0.138)	(0.094)	(0.1456)	(0.266)	(0.111)	(0.143)
# of observations	4,954	398	66	6,255	6,914	1,167	653	1,528	843	155	1,812	472
# of firms	1,486	116	15	1,754	2,160	335	217	436	269	52	537	131
F/Wald Statistics	21.59***	3.09***	4.74***	19.96***	37.01***	8.61***	5.45***	8.01***	3.51***	4.54***	7.57***	7.42***
	22	23	24	25	26	27	28	29	30	31	32	33
constant	3.676***	4.077***	4.026***	3.597***	4.915***	3.381***	2.609***	2.140***	3.6192	2.692***	1.754***	0.866
	(0.435)	(0.654)	(0.762)	(0.358)	(0.816)	(0.748)	(0.382)	(0.584)	(2.889)	(0.570)	(0.639)	(1.755)
lnva	0.168***	0.112***	0.067	0.066**	0.010	0.070*	0.105***	0.190***	0.024	0.121***	0.144***	-0.030
	(0.036)	(0.043)	(0.056)	(0.028)	(0.0489)	(0.041)	(0.033)	(0.032)	(0.063)	(0.046)	(0.055)	(0.141)
lnk	0.029	0.048	0.051**	0.008	0.031	0.032	0.033*	0.003	-0.029	0.023	-0.014	0.278*
	(0.019)	(0.033)	(0.025)	(0.014)	(0.030)	(0.021)	(0.019)	(0.023)	(0.183)	(0.019)	(0.041)	(0.143)
$\boldsymbol{x}$	-0.825**	0.084	-0.681**	-0.245	0.134	-0.213	-0.804***	-0.384*	-0.395	-0.917***	-0.189	-0.527
	(0.409)	(0.200)	(0.340)	(0.154)	(0.318)	(0.231)	(0.182)	(0.197)	(0.444)	(0.271)	(0.157)	(0.488)
$\boldsymbol{ln(n+\delta+x)}$	-0.525***	-0.419***	-0.367***	-0.411***	-0.596***	-0.420***	-0.392***	-0.251***	-0.136	-0.421***	-0.152	-0.268
	(0.043)	(0.079)	(0.086)	(0.047)	(0.105)	(0.115)	(0.056)	(0.082)	(0.171)	(0.073)	(0.107)	(0.184)
# of observations	4,028	3,423	1,996	5,138	637	2,490	4,617	2,424	494	2,100	1,249	358
# of firms	1,184	995	564	1,644	199	760	1,457	665	159	670	389	152
F/Wald Statistics	38.13***	6.02***	6.32***	14.56***	6.92***	8.72***	16.75***	12.14***	2.58***	11.04***	8.12***	3.26***

Notes: Robust standard errors are given in parentheses, and *, ** and *** indicate 10%, 5% and 1% significance level, respectively. A full set of time dummies is included in all estimations.