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Technology and Energy Substitution: A Path toward Climate Change Mitigation*

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Abstract

Mitigating climate change is critically linked to reducing an economy's reliance on fossil energy. This paper examines U.S. energy dependence, measured by its factor share, using a neoclassical framework systematically. We present the degree of *substitution* between different factors of production as a simple, explicit mechanism for climate change mitigation and for interpreting energy-saving technical change. With time-varying capital equipment-energy substitutability, changes in observed factor quantities alone can account for most of the variations in the income share of energy over 1963-2019. Advancing capital equipment access and quality and integrating the dynamic substitutability between energy and equipment into the design of climate policies can help economies achieve environmental goals.

Keywords: Elasticity of substitution, energy, climate change, technological change, capital-skill complementarity

JEL: E13, E23, E25, J24, Q41, Q42, Q54, Q55

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1 Introduction

Carbon dioxide (CO2) emissions are the main driver of global climate change, with fossil fuels (coal, natural gas, and petroleum) being the major source of human-based CO2 emissions (IPCC (2021)). In the U.S., the second-largest emitter globally, more than 90 percent of total CO2 emissions were from burning fossil fuels in 2019.[1] As emissions and atmospheric CO2 concentrations reach record levels, governments face increasing pressure to implement steeper emissions cuts. For example, in the U.S., these circumstances have led to actions such as rejoining the Paris Agreement, a global effort to significantly reduce greenhouse gas emissions.

Reducing carbon intensity, a crucial step towards lowering CO2 emissions, hinges on decreasing fossil energy intensity (Pindyck (2021))—the amount of energy consumed per dollar of GDP. However, fossil energy still accounted for 80 percent of U.S. total primary energy consumption in 2019, as high as a decade ago. While fossil energy use itself has seen limited reductions, fossil energy intensity has declined since the late 1970s partly due to gradual changes in the composition of GDP and the way it is produced.[2] Concurrently, the income share of fossil energy in the U.S., reflecting the proportion of national income attributed to energy, exhibits significant volatility with no clear trend. Much like fossil energy prices, it has fluctuated dramatically: increasing sharply after the first oil shock in the 1970s, plummeting in the 1980s, stabilizing in the 1990s, and rising again in the 2000s. This volatility highlights the uncertainty and lack of clarity in understanding the U.S. economy's reliance on fossil fuels.

This paper takes a macroeconomic approach to examine an economy's reliance on energy measured by its factor share, building on the work of Krusell et al. (2000). The goal is to provide a simple, explicit economic mechanism accounting for the historical variation in the U.S. income share of energy in terms of observed factor quantities over the past six decades. We then use our theory to quantitatively explore the extent to which the economy could move closer to achieving climate-related objectives.

We interpret U.S. data from the perspective of a production function for aggregate domestic output that has five-factor inputs—capital equipment, capital structures, skilled and unskilled labor, and fossil energy—and allow for different elasticities of substitution among these inputs. We distinguish between capital equipment and structures, as their relative

[1] Energy Information Administration, *Monthly Energy Review* and Our World in Data. The U.S. accounted for about 14 percent of global CO2 emissions in 2019.

[2] Services have become a larger share of GDP, whose production uses less energy than producing manufactured goods. Moreover, energy use has become more efficient, such as more fuel-efficient vehicles or more efficient heating and cooling systems.

prices and stock levels have grown at strikingly different rates. Moreover, the ratio of the quantity of capital equipment to the quantity of fossil energy exhibits a secular increase over the past six decades. Skilled and unskilled labor inputs also show differing trends, such as an increasing trend in the skill premium (the wage of skilled labor relative to that of unskilled labor). We assume that our technology is Cobb-Douglas over capital structures given its relatively stable factor share, and a nested constant elasticity of substitution (CES) function of the four remaining inputs–as such, it places no restrictions on their income shares over time and, in fact, can produce large fluctuations in incomes shares.

We first show that an aggregate production function featuring capital equipment-energy substitutability and energy-skill complementarity, meaning energy is more substitutable with capital equipment than with skilled labor, can help us understand the variation in the income share of energy in terms of observable factor inputs. This simple and explicit economic mechanism may have offsetting effects and may be important for understanding the historical trend in the factor share of energy.

We then estimate the parameters of the production technology by minimizing the distance between several model-implied variables and their data counterparts, such as the labor share or the energy share of income. Using income shares to help choose production technology parameters is a standard approach in the business cycle and growth literature (e.g., Prescott (1986)). We then construct factor prices given the time-series data on inputs and marginal products from the estimated production function. Using these prices and observable factor inputs, we form variables from the model, including the income share of energy, and compare the model predictions with those in the data.

We find that the key substitution elasticities are consistent with capital-energy substitutability and energy-skill complementarity. Our model successfully captures the long-run trend of the energy share. It also maintains consistency with the behavior of the U.S. labor market trends and the returns on physical capital over time. To gain further insight into the evolution of the energy share, we consider a historical decomposition and counterfactuals. They reveal that capital-energy substitutability is particularly important in driving the historical trend in the energy share, but capital-energy substitutability seems particularly important. For example, the enormous rise in the stock of equipment capital over the past six decades appears to have prevented a larger share of U.S. income from being directed to energy use.

The large short-run fluctuations in the energy share seem to be mostly driven by the changes in energy prices. By exploring global patents data, we show that the global share of low-carbon patents closely follows energy prices, providing evidence for innovations induced by energy price shocks. Motivated by this finding, we investigate time-varying substitutability between capital equipment and energy. We show that substitutability between capital equipment and energy has increased significantly since the mid-1970s, coinciding with higher average energy prices and higher average shares of clean patents relative to the mid-1970s. Thus, energy-saving technological progress—due to rising energy prices—may partly reflect omitted shorter term changes in equipment capital-energy substitutability.

Once we relax the assumption of constancy and account for the dynamic interchangeability between capital equipment and energy over time, coupled with plausible differences in substitution elasticities, the observed factor quantities better explain the fluctuations in the U.S. income share attributed to energy from 1963 to 2019. These insights are important for understanding U.S. energy reliance and, consequently, for drawing conclusions related to energy intensity and designing policies aimed at mitigating climate change.

To investigate the extent to which the economy can gravitate toward environmental targets, we extend our five-factor baseline model to a six-factor production function with non-fossil energy as an alternative energy source. We find that fossil and non-fossil energy sources exhibit a relatively high degree of substitutability, a scarcely estimated parameter in the literature. As a pivotal factor influencing carbon emissions, our attention zooms in on the implications of our extended model for the (fossil) energy intensity of output, particularly in the context of targets grounded in the globally embraced Paris Agreement. Under a set of assumptions, our model implies a decline of about 50 percent in U.S. fossil energy intensity below its 2005 level by 2030, suggesting alignment with the climate-related objectives. Striving for near-zero intensity, however, appears to necessitate several more decades. In essence, our analysis underscores the feasibility of achieving the 2030 target but reaching the 2050 goal seems to demand additional steps, such as further acceleration in equipment-specific technological advancements. Substitution is a powerful channel, and integrating the (dynamic) substitutability between equipment capital and energy into climate policy design is important. Bolstering the equipment capital stock to curb the economy's fossil energy intensity and, subsequently, its carbon intensity could also align well with the aspirations set forth by the current U.S. policy (e.g., the Inflation Reduction Act (IRA), which seeks historic investments to address climate change).

1.1 Relation to the Literature

The elasticity of substitution between factor inputs is crucial in understanding how changes in relative factor prices influence factor shares, as established by Hicks (1932). This concept is particularly relevant for analyzing the share of energy in income, given the fluctuating nature of energy prices and technological advancements (e.g., see Figure 5.4 left panel). In this paper, we present substitution as a simple, explicit economic mechanism for understanding the variations in the income share of energy over the past 60 years in terms of observable inputs. By disaggregating input data, considering their interactions, and focusing on how much changes in observed input quantities can deliver, we show that increasing substitutability between capital equipment and fossil energy since the mid-1970s coincides with rising fossil energy prices and global clean patent share. We find that with time-varying capital equipment-energy substitutability, changes in observed inputs alone can account for most of the variations in the income share of energy over the past 60 years. As such, the rapid growth in the stock of capital equipment seems to have prevented a larger income share of energy and can be a crucial factor for lowering the energy intensity and hence the carbon intensity of the economy.

Traditionally, the elasticity of substitution is considered time-invariant. However, recent studies suggest that this parameter varies over time. Miyagiwa and Papageorgiou (2007) show through a dynamic multi-sector growth model that the aggregate elasticity of substitution tends to increase with economic development. Oberfield and Raval (2021) empirically validate this variability, showing significant changes in elasticity across different industries. Our use of expanding window regressions captures both short-run fluctuations and long-term trends in the elasticity of substitution between equipment capital and energy. This approach provides a more granular understanding of how technical change and economic incentives can impact their substitutability, offering a dynamic view that reflects the evolving and volatile nature of the energy markets.

Acemoglu (2002a) emphasizes that the direction of technical change is influenced by the elasticity of substitution. Caselli and Coleman (2006) and Jones (2005) support this view, demonstrating that technological progress is often directed towards improving the substitutability of inputs. Hassler et al. (2021) expand on this by developing a quantitative macroeconomic theory that highlights how markets respond to the scarcity of natural resources through directed technical change. They show that the U.S. economy has historically had a very low short-run elasticity of substitution between energy and capital/labor, but a significantly higher long-run elasticity.[3]

Our work differs from Hassler et al. (2021) in several ways. First, we disaggregate the input side and emphasize substitution, particularly between energy and different types of capital and labor, as an explicit mechanism to understand movements in the energy share through observed factor quantities. While Hassler et al. (2021), similar to Atkeson and Kehoe (1999), provide theoretical insights into the microfoundation of short-run and long-

[3] On climate change and technical change see for example, Acemoglu et al. (2012), Fried (2018), Casey (2023), among others.

run energy elasticities, we allow the elasticity of substitution between energy and capital to vary over time in a reduced-form way, letting the data speak more directly. Second, by allowing for time-varying equipment capital-energy substitutability, our model accounts for much of the short-run fluctuations in the income share of energy, which Hassler et al. (2021) do not explicitly address. Our analysis suggests that energy-saving technical change may partly reflect omitted shorter-term changes in capital-energy substitutability. We show that increasing substitutability between equipment capital and energy since the mid-1970s coincides with rising energy prices and clean innovation, presenting evidence for a mechanism through which the economy responds to changes in energy markets and technology over shorter horizons. Similar to Krusell et al. (2000) providing an interpretation of skill-biased technical change à la Katz and Murphy (1992) based on observable factors, we provide a potential (reduced-form) observable factor-based interpretation of energy-saving technical change. Finally, we use our framework to assess the feasibility of achieving U.S. climate policy goals. Our work provides a complementary perspective, new evidence, and additional policy-relevant implications while understanding energy dependence through macroeconomic models.

We also contribute to the theoretical and empirical literature on input elasticities. There is a long-standing literature examining substitution possibilities between energy and non-energy inputs to inform policy and economic modeling (for example, Berndt and Wood (1975), Griffin and Gregory (1976), Pindyck and Rotemberg (1983), Kim and Loungani (1992), Atkeson and Kehoe (1999), van der Werf (2008), León-Ledesma and Satchi (2019), among others).[4] We explore different functional forms and estimate substitution elasticities that fit disaggregated U.S. data over a long time period (1963-2019) using different methods. Capital equipment and energy are complements in the short-run and substitutes in the long-run, overall in line with the assessment of a higher long-run elasticity between energy and non-energy inputs.[5] Additionally, our paper contributes to the limited literature estimating the elasticity of substitution between clean (non-fossil) and dirty (fossil) energy inputs. Papageorgiou et al. (2017) provide estimates of this elasticity using sector-level data from multiple countries. More recently, Jo and Miftakhova (2024) develop a model with an endogenous elasticity of substitution between clean and dirty energy, starting from an

[4]Note that studies differ across several dimensions that can affect the results, including the functional forms considered, the estimation techniques used, the type of data considered and time periods examined. For example, Koetse et al. (2008) provide a meta-analysis synthesizing the empirical literature on capital-energy substitution with studies published from mid-1970s through early 2000s, revealing significant variations in substitution elasticity estimates across different models, regions, and time periods.

[5]Building on Polgreen and Silos (2008), Polgreen and Silos (2009) investigate the relationship between oil prices and the skill premium. They explain the negative correlation between the two by short-run capital-energy complementarity.

initial value of 1.9 based on French manufacturing data. While these studies use different methodologies and data sources, they find elasticities greater than unity, in line with our estimate. Our work provides an economy-wide estimate based on U.S. data and explores the implications for U.S. climate policy.

The derived demand for inputs, including energy, depends on the substitution possibilities among inputs allowed by the production technology. Hence, elasticities between energy and non-energy inputs are critical for the quantitative climate economy literature, where elasticities considered are generally based on aggregate data. Studies often assume energy is combined with capital and labor in a Cobb-Douglas production function, which seems consistent with long-run data on energy use and prices but not with short-run data (e.g., Atkeson and Kehoe (1999), Hassler et al. (2021), Casey (2023)). Our paper contributes by providing a structural interpretation of disaggregated data based on estimates of substitution elasticities and emphasizing the importance of substitution, particularly taking into account capital equipment-energy substitutability when designing climate policy. Our work highlights the significance of this channel for addressing climate change.[6]

The paper is organized as follows. In Section 2, we discuss the quantity and factor price data we use in our analyses. In Section 3, we present the baseline model. In Section 4, we describe the quantitative methodology. In Section 5, we present our estimation results, extended model, and climate policy implications. In Section 6, we conclude. The online Appendix presents the construction of the data and additional results.

2 Data

We focus on the U.S. economy and review the changes in the prices and quantities of capital, labor, and energy inputs using annual data from 1963 to 2019.[7] Details on the data and construction of the variables can be found in the Appendix A.1. Starting with fossil energy, we consider three types of fossil fuels: coal, crude oil, and natural gas. We obtain an accompanying real price index, P_t, and define the energy share as E_tP_t/Y_t, where E_t is energy use and Y_t is real GDP net of the net export of fossil fuels.[8] As shown by the dashed red line in Figure 2.1, the income share of energy has fluctuated between 1 and 8 percent, yet the overall long-run trend is relatively stable. The share increases considerably

[6] In a recent paper, Moll et al. (2023) highlight the importance of substitution in reducing the economic impact of a large input supply shock, namely the German cut-off from Russian gas.

[7] The start of our time frame is constrained by the CPS data we use to construct the labor inputs.

[8] Our approach in constructing the energy use series is similar to that of Hassler et al. (2021). Output here can be interpreted as GDP minus the value of energy use outside of domestic production. Due to lack of consistent data on household use of energy as a final good, which is small compared with the total, we set household use to zero.

after the first oil shock, then falls dramatically in the 1980s. It remains low and relatively stable throughout the 1990s before increasing again in the 2000s and then exhibiting another dramatic decline in the mid-2010s. In contrast, the real price of fossil energy input (black line) shows a clear increasing trend. Despite these differing long-term trends, the price and the income share of energy strongly and positively comove.

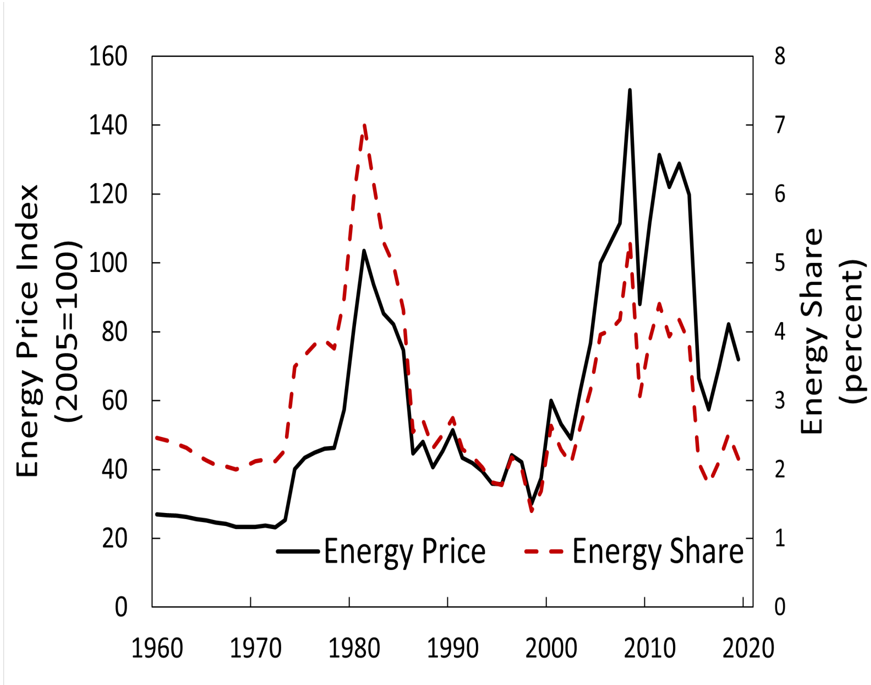

Figure 2.1: Income Share of Fossil Energy and Real Price of Fossil Energy

We consider two types of capital (structures and equipment), as their prices relative to consumption and their stock levels have grown at strikingly different rates. Capital equipment includes intellectual property products, as is standard in the literature. The top-left panel of Figure 2.2 shows that the relative price of equipment capital has fallen significantly since the early 1960s, while the relative price of structures has remained relatively stable over this period. This long-run decline in the relative price of equipment capital can be interpreted as the equipment-specific technological progress; see, for example, Greenwood et al. (1997). Consistent with this substantial equipment-specific technological change, the stock of capital equipment rose to a level about 80 times that of its 1963 level by 2019, while the stock of structures grew to a level only about 5 times that of its 1963 level, the top-right panel of Figure 2.2.

We also look into the ratio of the quantity of capital equipment to the quantity of fossil energy input. The middle panel of Figure 2.2 shows that this ratio exhibits a secular increase over the past six decades. As we will show, this ratio is important in our analysis, since it

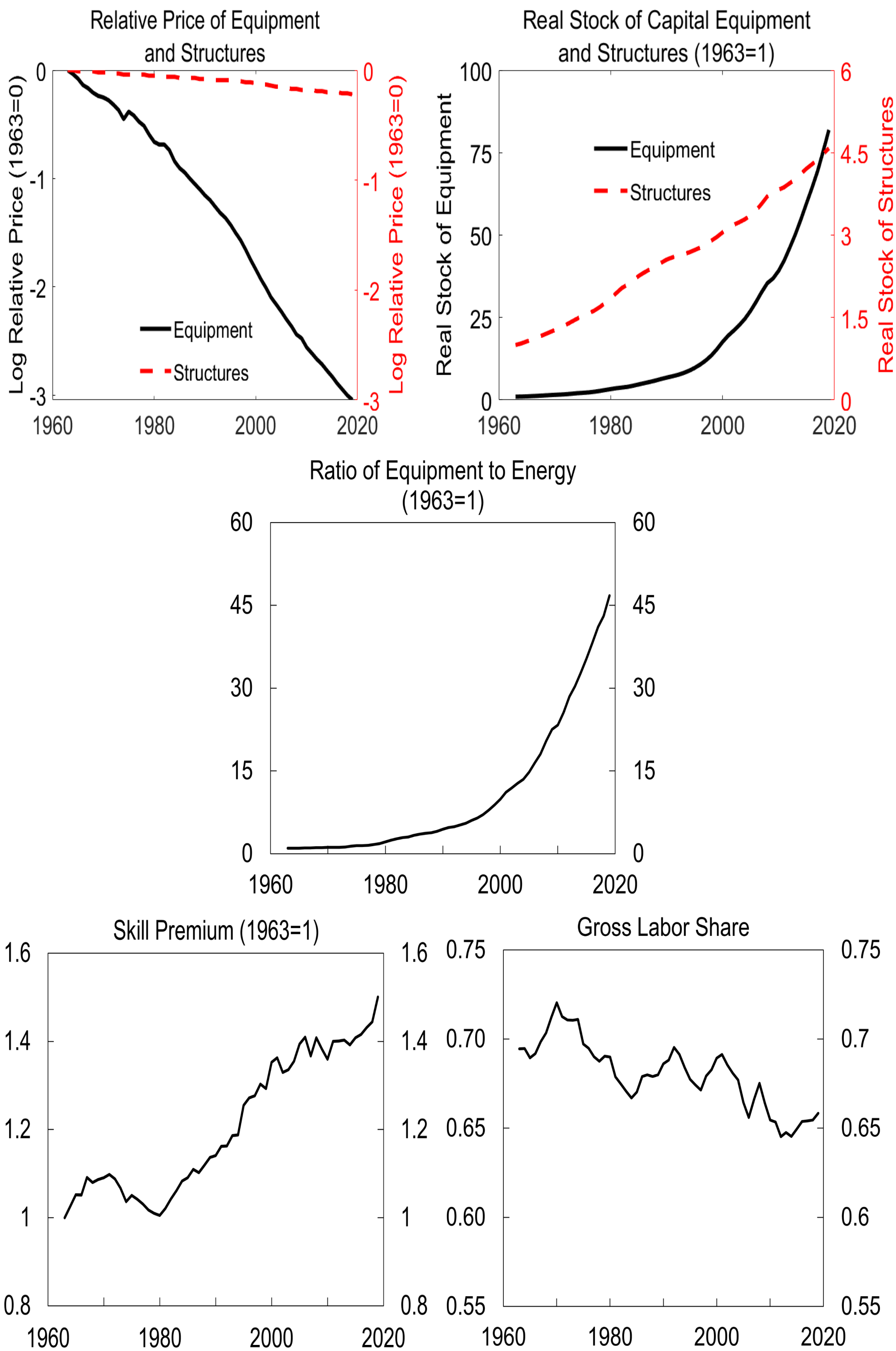

Figure 2.2: Stock and Prices of Capital Equipment and Structures, the Ratio of Capital Equipment to Energy, Skill Premium, and Gross Labor Share

affects the trends in the income share of energy through capital-energy substitutability.

We also differentiate between two types of labor (skilled and unskilled), and define skill on the basis of college degree attainment. We distinguish between labor types because the two types of labor also show differing trends and potentially have different interactions with the energy input. While there is a continuous increase in skilled labor input relative to unskilled labor input, the skill premium -the wage of skilled labor relative to that of unskilled labor- increased by about 50 percent since the early 1960s, as shown in the bottom-left panel of Figure 2.2.[9] Note that as a consequence of rising skilled labor input and the relative wage of this labor type, the income share of skilled labor exhibits a secular increase over the past six decades. As we will discuss later, this share also helps us understand the trends in the income share of energy.

Finally, the bottom-right panel of Figure 2.2 shows the share of income earned by aggregate labor, which is defined as the ratio of labor income (wages, salaries, and benefits) to the sum of labor income plus capital income (depreciation, corporate profits, net interest, and rental income of persons). It presents a declining trend, one of the striking features of the recent U.S. economy that has been widely discussed in the literature.[10]

We interpret these data from the perspective of a production function for aggregate domestic output that has five inputs. In the next two sections, we first develop such a framework and then estimate the model on the U.S. data presented here.

3 Baseline Model

We build on the work of Krusell et al. (2000) by introducing fossil energy as a factor of production. We focus on the aggregate production function and abstract from modeling the household sector for simplicity. Our approach involves developing a five-factor production function and estimating the parameters of that particular production technology by minimizing the distance between several model-implied variables and their data counterparts. We then construct factor prices given the time-series data on inputs and marginal products from the estimated production function. Using these prices and observable factor inputs, we form variables from the model, including the income share of energy, and compare the model predictions with those in the data.

[9] Many studies examine why the skill premium has risen during a period with significant growth in the relative supply of skilled labor, and argue that skill-biased technological change must be an important factor (e.g. Katz and Murphy (1992), Acemoglu (2002b)). Krusell et al. (2000), on the other hand, address this question on the basis of observables and through capital-skill complementarity. McAdam and Willman (2018) nest these two explanations, skill-biased technical change and capital-skill complementarity, using a multiequation production and technology system.

[10] Some recent work on this topic includes Orak (2017) and Glover and Short (2020), among many others.

Our neoclassical production technology for the U.S. economy, Y_t, has constant returns to scale and distinguishes between equipment capital ($K_{eq,t}$) and structures capital ($K_{s,t}$), as well as skilled ($L_{s,t}$) and unskilled labor inputs ($L_{u,t}$), and it includes fossil energy (E_t). The very different paths of the quantities and relative prices of these variables presented in the previous section motivate these distinctions. Furthermore, we allow for, but do not impose, different substitution possibilities between inputs.

There are three final goods in this economy: consumption, structures investment, and equipment investment. Consumption and structures are produced with a constant returns-to-scale technology, and their prices are normalized to 1.[11] Equipment is produced with the same technology scaled by equipment-specific productivity, q_t. With perfect competition, we have the relative price of equipment capital equal to $\frac{1}{q_t}$. So we consider the relative price of equipment capital as the (inverse) proxy for technological progress, a common interpretation in the literature. Under these assumptions, aggregate resource constraint ensures that aggregate output, Y_t, equals total spending on consumption and investments on structures and equipment.

We must first choose a functional form for the production function that represents the U.S. economy. To simplify and given capital structures' relatively stable factor share, we assume that our technology is Cobb-Douglas over capital structures and a CES function of the four remaining inputs. One can nest $K_{eq,t}, L_{s,t}, L_{u,t}$, and E_t within a CES function in different ways. In determining a baseline specification, we follow a meticulous approach: Compare model fits of data for several different specifications and choose the one that yields the best joint fit for a set of target variables—the skill premium, the labor share, and the energy share. We will present and discuss our model and estimation approaches in detail later in the paper, but the following is worth mentioning. First, these target variables describe important features of the U.S. economy (as presented earlier). Second, the model counterparts of the target variables are obtained using the firm's first-order conditions for factors of production. Note that we use generalized method of moments (GMM) to estimate the parameters of the production functions presented below.

More specifically, we present results on four different nested-CES functions combining $K_{eq,t}, L_{s,t}, L_{u,t}$, and E_t in different ways.[12] The far left column in Table 3.1 shows the specifications we consider in functional forms. For example, one specification (specification I) combines the energy input with capital equipment first, which we call *capital-energy services*. *Capital-energy services* are then combined with skilled labor, which is then combined with

[11] This is a reasonable assumption because the relative price of structures has not changed much during the period of this study, as shown in the previous section.

[12] Note that we considered all potential nestings and chose to present those four specifications, as the others yielded inconsistent, not well-defined elasticities.

unskilled labor with different elasticities of substitution between equipment capital and energy, between skilled labor and capital-energy services, and between unskilled labor and the combined output of capital-energy services and skilled labor. Another specification (specification II) combines the energy input with unskilled labor in a CES composite and skilled labor and equipment capital in another CES composite. These two CES composites are then combined with different elasticities of substitution between unskilled labor and energy, between equipment capital and skilled labor, and between those two composites.

The four columns in Table 3.1 present the normalized root mean squared errors (NRMSEs) for the three target variables as well as the total NRMSEs under these specifications. As shown in the table, specifications I and II stand out with lower total NRMSEs (of around 0.5) than specifications III and IV, leading us to eliminate specifications III and IV. To make a more informed decision in choosing between specifications I and II, we also look at the time-series model fits of those specifications against their data counterparts, presented in Figure A.1 in the Appendix A.2. Together, Table 3.1 and Figure A.1 suggest that both specifications have a similar fit for the skill premium. While specification I fits the labor share slightly better, specification II has a better fit for the energy share. Overall, these suggest that specifications I and II are similarly successful in fitting the data. However, specification II turns out to be statistically unstable, as it computationally struggles to identify the elasticity parameter between unskilled labor and energy inputs.[13] Specification I, by contrast, gives stable estimates. As a result, we choose specification I as our baseline technology.[14]

Table 3.1: Normalized RMSEs for the Skill Premium, the Labor Share, and the Energy Share

Technology Specification	**Skill Premium**	**Labor Share**	**Energy Share**	**Sum**
I. $Y = H_1(K_{st}, g_1[U, f_1(h_1(E, K_{eq}), S)])$	0.041	0.023	0.454	0.518
II. $Y = H_2(K_{st}, g_2[f_2(U, E), h_2(K_{eq}, S)])$	0.041	0.028	0.399	0.468
III. $Y = H_3(K_{st}, g_3[S, f_3((h_3(K_{eq}, E)), U)])$	0.460	0.090	0.794	1.344
IV. $Y = H_4(K_{st}, g_4[U, f_4(K_{eq}, h_4(S, E))])$	0.155	0.049	0.801	1.005

Note: H_i denotes a Cobb–Douglas function that combines capital structures with the remaining four inputs in different nestings. g_i, f_i, and h_i represent CES nestings of the enclosed inputs, for $i \in \{1, 2, 3, 4\}$. RMSE stands for the root mean squared error, and normalized RMSE is the RMSE divided by the mean value of the corresponding variable.

The baseline specification is also very intuitive and interpretable. One can interpret this

[13]In specification II, the energy-related parameters are statistically insignificant and the estimates are highly sensitive to adding a few years of observations or changes in initial points.

[14]We also compared baseline model results with a model in which capital and labor are aggregated. In that case, not only did the model fit worsen, but we also could no longer explain certain features of the U.S. economy, such as the increasing wage inequality.

type of production technology along the lines of Goldin and Katz (1998) as follows. Production takes place in three stages. In the first stage, new technologies (or new equipment) adopt to work with energy efficiently in the firm. In the second stage, skilled workers adopt those new technologies and ensure that they work efficiently. The third and final stage consists of maintenance and the more mechanical part of the production process that involves unskilled labor.

Now, we can introduce the baseline technology for our analysis:

$$\begin{aligned} Y_t &= A_t G\left(K_{s,t}, K_{eq,t}, E_t, L_{u,t}, L_{s,t}\right) \\ &= A_t K_{s,t}^{\alpha}\Big[\mu L_{u,t}^{\sigma} + (1-\mu)\big(\lambda[\xi K_{eq,t}^{\nu} + (1-\xi)E_t^{\nu}]^{\frac{\rho}{\nu}} + (1-\lambda)L_{s,t}^{\rho}\big)^{\frac{\sigma}{\rho}}\Big]^{\frac{1-\alpha}{\sigma}} \end{aligned} \tag{3.1}$$

where A_t is neutral technological change at time t. In this specification, μ, λ, and ξ are parameters governing income shares. σ, ρ, and ν govern elasticities of substitution between different factors of production, and are restricted to lie in $(-\infty, 1)$ to maintain strict quasi-concavity of the production function. We define the elasticity of substitution between equipment capital and energy input as $\frac{1}{1-\nu}$, the elasticity of substitution between skilled labor and capital-energy services as $\frac{1}{1-\rho}$, and the elasticity of substitution between unskilled labor and composite output of capital-energy services and skilled labor as $\frac{1}{1-\sigma}$.[15] Note that when either of σ, ρ, or ν is zero, their corresponding nesting is Cobb–Douglas. Finally, $L_{s,t}$ and $L_{u,t}$ are skilled and unskilled labor inputs in efficiency units, respectively. They are combinations of raw labor hours, $h_{s,t}, h_{u,t}$, and efficiencies as follows:

$$\begin{aligned} L_{s,t} &= h_{s,t} e^{\varphi_{s,t}} \\ L_{u,t} &= h_{u,t} e^{\varphi_{u,t}}, \end{aligned}$$

where $\varphi_{s,t}$ and $\varphi_{u,t}$ denote (unmeasured) efficiencies of skilled and unskilled labor, respectively.

3.1 The Income Share of Energy

We can now use the model to examine how the income share of energy and factor inputs are related.

Given that factor prices are equal to marginal products, one can express the ratio of the

[15] There are other ways of defining elasticities between inputs. The definition we consider here assumes that no other factors change except the pair of factors considered.

income shares of skilled labor and energy as follows:

$$\frac{L_{s,share,t}}{E_{share,t}} = \frac{w_{s,t}h_{s,t}}{p_{E,t}E_t} = \frac{G_{L_{s,t}}h_{s,t}}{G_{E,t}E_t},$$

where $L_{s,share}$ and E_{share} are the income shares of skilled labor and energy and G_{L_s} and G_E are the marginal products of skilled labor and energy, respectively. Then, the model-implied energy share can be expressed as a function of the input ratios, the income share of skilled labor, and the technology parameters:

$$E_{share,t} = \frac{\lambda(1-\xi)}{(1-\lambda)}\left(\frac{E_t}{L_{s,t}}\right)^{\rho}\left(\xi\left(\frac{K_{eq,t}}{E_t}\right)^{\nu} + (1-\xi)\right)^{\frac{\rho-\nu}{\nu}} L_{s,share,t}. \tag{3.2}$$

In Section 2, we present that input ratios have shown significant trends over the past six decades. In this context, equation 3.2 shows how changes in input ratios can affect the income share of energy. An increase in the abundance of skilled labor relative to energy use, ceteris paribus, would increase the income share of energy if and only if $\rho < 0$, which implies (absolute) complementarity between skilled labor input and capital-energy services. Moreover, an increase in the stock of equipment capital relative to energy use, ceteris paribus, would lead to a rise in the energy share if and only if $\rho > \nu$. Finally, the energy share is increasing in the income share of skilled labor for all admissible parameter values.

To further illustrate the implications of our model for the energy share, we log-linearize equation 3.2 and then differentiate with respect to time. After some algebra, we obtain[16]:

$$\begin{aligned} g_{E_{share,t}} \simeq\; & \underbrace{\rho(g_{E,t} - g_{\psi_{s,t}} - g_{h_{s,t}})}_{\text{energy-skill complementarity effect}} \\ & + \underbrace{(\nu-\rho)\xi\Gamma\left(g_{E,t} - g_{K_{eq},t}\right)}_{\text{capital-energy substitutability effect}} \\ & + \underbrace{g_{L_{s,share,t}}}_{\text{skilled labor share effect}}, \end{aligned} \tag{3.3}$$

where $g_{x,t}$ denotes the growth rate of variable x at time t. Equation 3.3 gives us a simple way to use our model to understand how changes in factor quantities and substitution elasticities affect the income share of energy. The first term, $\rho(g_{E,t} - g_{h_{s,t}} - g_{\psi_{s,t}})$, depends on the growth rate of skilled labor in efficiency units relative to the growth rate of energy use. The relatively faster growth of skilled labor in efficiency units can increase the energy share if and

[16] Here, $\Gamma = \left(\xi + (1-\xi)\left(\frac{\bar{E}}{\bar{K}_{eq}}\right)^{\nu}\right)^{-1}$ is a constant term, where $\bar{K}_{eq}$ and $\bar{E}$ are average values of equipment capital and energy input, respectively.

only if $\rho < 0$. So we call this term the *energy-skill complementarity effect*. The second term, $(\nu - \rho)\xi\Gamma\left(g_{E,t} - g_{K_{eq},t}\right)$, is the *capital-energy substitutability effect*. It involves the growth in equipment capital relative to the growth of energy use. If $\nu > \rho$, energy is more substitutable with equipment capital than is skilled labor. In this case, faster growth in equipment tends to lower the growth of energy share as it lowers the relative demand for energy. Finally, $g_{L_{s,share}}$ is the growth rate of skilled labor share. An increasing skilled labor share increases the energy share. We call this component the *skilled labor share effect*. Given the large increase in the stock of equipment capital relative to energy use and the secular increase in skilled labor share we observe in the U.S. data, the latter two channels may have offsetting effects on the U.S. energy share if $\nu > \rho$.

To summarize, we present mechanisms that explain variations in the income share of energy in terms of observable factor inputs. Next, we estimate our model to obtain elasticities and assess the role of substitution elasticities. Furthermore, we will test if our baseline production function can account for changes in the energy share while aligning with key U.S. economic trends, including a declining labor share, an increasing wage-bill ratio, and reasonable rates of return on capital—elements frequently used to calibrate aggregate production functions in macroeconomics.

4 Quantitative Analysis

4.1 Estimation of the Baseline Model

To estimate the parameter values of the baseline production technology, presented in equation 3.1, we primarily use the simulated pseudo maximum likelihood estimation (SPMLE) procedure to maintain comparability of our results with those of Krusell et al. (2000) and Ohanian et al. (2023).[17] We also use GMM to estimate the parameters as a robustness check.[18]

For the SPMLE methodology, we need to specify two stochastic elements to close the model and ensure that the likelihood is non-singular. The first stochastic element is the relative price of equipment capital, which affects the rate of return on equipment investment,

[17] A complete description of this estimation methodology is outside the scope of this paper. Interested readers are referred to Ohanian et al. (2000) and Krusell et al. (2000) for detailed descriptions of the methodology. For an alternative procedure, see Polgreen and Silos (2008).

[18] GMM offers flexibility in terms of model target selection and is relatively simple to implement. Unlike the SPMLE methodology, GMM does not require the full likelihood of the model. It enables the estimation of modified versions of the baseline production technology or allows for estimating the baseline model with alternative targets, without the need to specify stochastic components. Importantly, as we show later, both SPMLE and GMM methodologies yield very similar estimates. This similarity suggests that differences in estimation techniques are unlikely to influence the results significantly.

and the second one is the (unobserved) efficiencies of the skilled and unskilled labor. Note that in our partial equilibrium framework, the firm treats energy as a contemporaneous input like labor, hence we do not specify a stochastic process for the price of energy. To specify the first process, we consider a "no arbitrage" condition that sets the expected net rate of return on investment in structures equal to that on investment in equipment:

$$\underbrace{A_{t+1}G_{st,t+1} + (1 - \delta_{st,t+1})}_{\text{expected return on structures}} = \underbrace{q_t A_{t+1} G_{eq,t+1} + (1 - \delta_{eq,t+1}) E\left(\frac{q_t}{q_{t+1}}\right)}_{\text{expected return on equipment capital}}. \tag{4.1}$$

Structures and equipment capital depreciate at time-varying rates $\delta_{st,t}$ and $\delta_{eq,t}$, respectively, whose paths are assumed to be known by the firm. $G_{st,t+1}$ and $G_{eq,t+1}$ denote the marginal products of structures and equipment capital at time $t+1$, respectively. A_{t+1} is the neutral total factor productivity at time $t+1$, which can be identified simply as a residual given the output from data and model parameters and observed inputs as follows: $\frac{Y_{t+1}}{G(K_{st,t+1},K_{eq,t+1},E_{t+1},L_{u,t+1},L_{s,t+1})}$. Finally, following Krusell et al. (2000), and to simplify the estimation, we assume that there is no risk premium, tax treatments for these two types of capital are the same, and $(1-\delta_{eq,t+1})E\left(\frac{q_t}{q_{t+1}}\right) = (1-\delta_{eq,t+1})\frac{q_t}{q_{t+1}} + \varepsilon_t$, where ε_t is assumed to be normally distributed with mean zero and variance σ_ε^2.[19]

The second stochastic element is the (unobserved) efficiencies of the skilled and unskilled labor. We assume that $\varphi_{s,t}$ and $\varphi_{u,t}$ follow

$$\varphi_{i,t} = \varphi_{i,0} + \omega_{i,t}, \tag{4.2}$$

where $i = s, u$. $\varphi_{s,0}$ and $\varphi_{u,0}$ correspond to average log levels of efficiencies for skilled and unskilled labor, and $\omega_{s,t}$ and $\omega_{u,t}$ are labor efficiency shocks for skilled and unskilled labor, respectively. We assume that these shocks have a multivariate normal distribution with zero mean and covariance matrix $\Omega = \begin{bmatrix} \eta_\omega^2 & 0 \\ 0 & \eta_\omega^2 \end{bmatrix}$ where η_ω^2 is the common variance. Given that we focus on whether changes in observable variables can account for trend changes in the energy share, for comparability with related studies and to keep the number of estimated parameters reasonable, our baseline specification has no trend variation in labor quality of the two types.[20]

[19] Krusell et al. (2000) explore the implications of the tax treatments assumption by constructing different tax measures for both capital types and applying those rates to equation 4.1. They report that their results remained very similar.

[20] Alternatively, we could allow for trend changes to efficiencies of both labor types. When trend changes are allowed, we obtain a much smaller degree of capital-skill complementarity, because skill-biased technological change plays an important role in accounting for rising income inequality (see, for example, Katz and Murphy (1992)). However, Krusell et al. (2000) and Orak (2017) argue that the estimated difference between trend

Now, we can describe the rest of the model equations to be estimated along with the estimation process. The estimation is done in three steps. In the first step, we only estimate energy-related parameters: the weight parameter, ξ, and the parameter governing the substitution elasticity between energy use and equipment capital, ν. The reason is that these parameters can be estimated by ordinary least squares (OLS) using a simple structural relationship that is based on income shares implied by the firm's first-order conditions for renting equipment capital and using energy. Using income shares to choose production technology parameters is a standard approach in macroeconomics; see, for example, Prescott (1986). More specifically, we use:

$$\frac{r_{eq,t}K_{eq,t}}{p_{E,t}E_t} = \frac{\xi}{1-\xi}\left(\frac{K_{eq,t}}{E_t}\right)^{\nu}, \tag{4.3}$$

where $r_{eq,t} = A_t G_{K_{eq,t}}$ is the rental rate on equipment capital and $p_{E,t} = A_t G_{E_t}$ is the price of energy input, with $G_{i,t}$ denoting the marginal product of input i at time t. Using equation 4.3 to estimate the energy-related parameters reduces the burden of estimation with a large number of parameters and slightly improves the model fit for the income share of energy.[21] Namely, we take the log of equation 4.3 and estimate it using OLS.[22] The resulting estimated regression is as follows:

$$\ln \widehat{\frac{r_{e,t}K_{e,t}}{p_{E,t}E_t}} = \underset{(.1081)}{1.7301} + \underset{(.0465)}{0.0555} \ln \frac{K_{e,t}}{E_t}, \tag{4.4}$$

where the values in parentheses are standard errors. It yields $\xi = 0.8494$ and $\nu = 0.0555$ in the inner CES between equipment capital and energy use. In other words, the elasticity of substitution between equipment capital and energy is 1.06. This value indicates slightly more substitutability than the Cobb-Douglas case, consistent with the long-run estimates presented in the literature (see, for example, Koetse et al. (2008)).[23] However, with a $p-value$

growth rates of skilled and unskilled labor quality is implausibly large in this case, which is hard to justify given that the efficiency of labor is not measurable.

[21] One could also estimate ν and ξ along with the rest of the parameters considering the energy share as the fourth targeted moment, which corresponds to specification I in Table 3.1. However, estimating ν and ξ by exploiting the simple relationship between the income shares presented in equation 4.3 improves the model fit of the energy share by about 13 percent, reducing the normalized RMSE of this variable from 0.454 to 0.394.

[22] Polgreen and Silos (2009) follow a similar approach. The construction of the series used in the regression is described in the Appendix.

[23] One might consider if the substitutability between capital equipment and energy primarily reflects interactions between capital equipment and inputs other than energy, especially given the substantial accumulation of capital equipment in recent decades. To explore this, we ran regressions similar to equation 4.3 for equipment capital against other factors of production. Results show that capital equipment is weakly

of 0.238, ν is statistically not different from zero, suggesting that the Cobb-Douglas case cannot be conclusively rejected.

In the second step, we regress both types of labor inputs and energy use on the current and lagged stocks of both types of capital, the lagged relative equipment capital price, a time trend, the lagged price of energy, and the lagged value of a leading business cycle indicator of the Conference Board. The purpose of this stage is to control for the possible dependence of supplies of labor inputs and energy use on general macroeconomic shocks. We then use the fitted values from these regressions in the third (SPMLE) step. However, when assessing the model fit, we use actual (non-instrumented) labor and energy inputs to investigate how much of the changes in the energy share and other macroeconomic variables can be explained by observed variables.

In the third step, we choose a set of parameters that minimize the distance between actual data and model outcomes across several targeted variables. Our targets include the wage-bill ratio (the income share ratio of skilled to unskilled labor), the gross labor share, and the no-arbitrage condition, which ensures equal expected rates of return on both types of capital. We chose these targets because they are crucial for capturing key characteristics of the U.S. economy, as previously discussed. This selection process forms the basis of our baseline estimation and yields the energy share as a not directly targeted outcome. Alternatively, we experimented with targeting the energy share instead of the labor share. The results of this approach, detailed in Appendix Figure A.2 and Table A.1, indicated a deteriorating model fit. Given the trade-offs and our preference for deriving the energy share as an indirectly targeted outcome, along with the ability of our production technology in equation 3.1 to estimate energy-related parameters (ν and ξ) using simple OLS regression, we opted for the baseline estimation approach.

The three targets we consider in the baseline estimation are:

1. Wage-bill ratio:

$$\underbrace{\frac{w_{s,t}h_{s,t}}{w_{u,t}h_{u,t}}}_{\text{data}} = \underbrace{wbr_t(X_t, \varphi_{u,t}, \varphi_{s,t}; \Upsilon)}_{\text{model}}, \tag{4.5}$$

substitutable with structures (elasticity of 1.1), complementary with skilled labor (elasticity of 0.8), and strongly substitutable with unskilled labor (elasticity of 1.3). These findings suggest that the observed increase in equipment capital does not automatically translate to broad substitutability across all remaining inputs. Therefore, it appears that the relationship between equipment capital and energy inputs is not merely a byproduct of interactions between equipment capital and non-energy inputs. That being said, future research exploring cross-industry data could enrich our understanding of how energy substitutes for other inputs in different sectors.

2. Labor share:

$$\underbrace{\frac{w_{s,t}h_{s,t} + w_{u,t}h_{u,t}}{Y_t}}_{\text{data}} = \underbrace{lshare_t(X_t, \varphi_{u,t}, \varphi_{s,t}; \Upsilon)}_{\text{model}}, \tag{4.6}$$

3. No-arbitrage condition:

$$\underbrace{q_t A_{t+1} G_{eq,t+1} + (1 - \delta_{eq,t+1}) \left(\frac{q_t}{q_{t+1}} \right) + \epsilon_t}_{\text{expected return on equipment capital}} - \{\underbrace{A_{t+1} G_{st,t+1} + (1 - \delta_{st,t+1})}_{\text{expected return on structures}}\} = 0. \tag{4.7}$$

In equations 4.5 and 4.6, the left-hand sides are data, and the right-hand sides are their model equivalents based on income shares. They are implied by the firm's first-order conditions for hiring skilled and unskilled labor as a function of observable inputs $X_t = \{K_{st,t}, K_{eq,t}, h_{u,t}, h_{s,t}, E_t, \delta_{eq,t}, \delta_{st,t}\}$; unobservable labor efficiencies $\varphi_{u,t}$ and $\varphi_{s,t}$; and a set of parameters $\Upsilon = \{\sigma, \rho, \alpha, \mu, \lambda, \varphi_{u0}, \varphi_{s0}, \eta_\epsilon, \eta_\omega\}$. Equation 4.5 is the ratio of earnings of skilled workers to unskilled workers. Equation 4.6 specifies the total share of labor income defined by marginal products from the production function. The goal is to choose the maximum value of the log-likelihood function that will minimize the distance between left (data) and right (model) sides while also maintaining reasonable ex-post rates of returns on the two types of capital (as targeted in the no arbitrage condition in equation 4.7).

So the estimation of the baseline model using SPMLE consists of a non-linear state-space model with equations 4.5 through 4.7 as the measurement equations and equation 4.2 as the transition equation. The number of parameters to be estimated can be reduced by calibrating some of them. We calibrate time-varying depreciation rates using the NIPA tables for the capital stock and capital consumption. The average depreciation rate is 0.028 for structures and 0.148 for equipment capital. We assume that the future depreciation rates are known.[24] To calibrate σ_ε, we estimate an ARIMA model for the relative price of equipment capital and set σ_ε equal to $(1 - \bar{\delta}_{eq})$ times the standard error of the residuals of this ARIMA model. Given that we obtained ν and ξ using OLS above, we fix their values. Finally, given that μ, λ, ξ, φ_{u0}, and φ_{s0} can act as scaling parameters, we choose to normalize $\varphi_{s,0}$.

All these left us with seven parameters to be estimated: σ and ρ, parameters governing the substitution elasticities; μ and λ, parameters governing weights; α, income share of structures; $\varphi_{u,0}$, average efficiency of unskilled labor; and η_ω^2, the variance of the labor efficiency shocks. Next, we present and discuss our results.

[24] As reported in Ohanian et al. (2023), using constant depreciation rates has no visible imprint on the results.

5 Results

We estimate the parameters for the entire 1963–2019 period using SPMLE. Table 5.1 presents these baseline estimates with asymptotic standard errors in parentheses along with the estimate for ν, governing the elasticity of substitution between energy and capital equipment, obtained via OLS. Our elasticities imply energy-skill complementarity ($\rho < 0$) and equipment capital-energy substitutability ($\nu > \rho$). The elasticity of substitution between capital equipment and energy, however, suggests slightly more substitutability than the Cobb-Douglass case.

Table 5.1: Parameter Estimates, Baseline

	σ	ρ	α	η_ω	ν
Value	0.431	−0.363	0.094	0.248	0.056
(Std. error)	(0.032)	(0.040)	(0.002)	(0.055)	(0.047)

More specifically, the estimate for the elasticity of substitution between unskilled labor and the composite of skilled labor and capital-energy services, $\frac{1}{1-\sigma}$, is around 1.76, while the estimate for the elasticity of substitution between skilled labor and capital-energy services, $\frac{1}{1-\rho}$, is about 0.73. Both estimates are consistent with the theory of capital-skill complementarity and hence in line with the estimates reported in Ohanian et al. (2023). The income share of capital structures, α, is also close to the value observed in the data.[25] The estimate for the elasticity of substitution between capital equipment and energy is 1.06, close to the long-run estimate discussed in Hassler et al. (2021).

It is worth noting that although we use annual data, our elasticity estimates should be interpreted as long-run estimates. This attribute is due to the estimation methodology we employ, which relies on minimizing the distance between the model-implied trends and their data counterparts rather than exploiting year-to-year fluctuations in the data. This distinction will be clearly seen in the results we present next, where the model captures the long-run trends reasonably well, while missing large short-run fluctuations in the energy share. To be consistent with the rest of the parameters estimated, the nature of our estimate for ν is also long term, as we do not detrend data while running the OLS regression in equation 4.4. Should we use differenced data instead, we would obtain $\nu = -0.858$, which implies a high degree of complementarity between equipment capital and energy, in line with

[25] Using the "Total Factor Productivity - Capital details for major sectors and industries" table of the Bureau of Labor Statistics and our measure of total capital income share, we calculate the average income share of structures capital for the private non-farm business sector over the period between 1987 and 2019 to be 10.6 percent.

short-run estimates.[26]

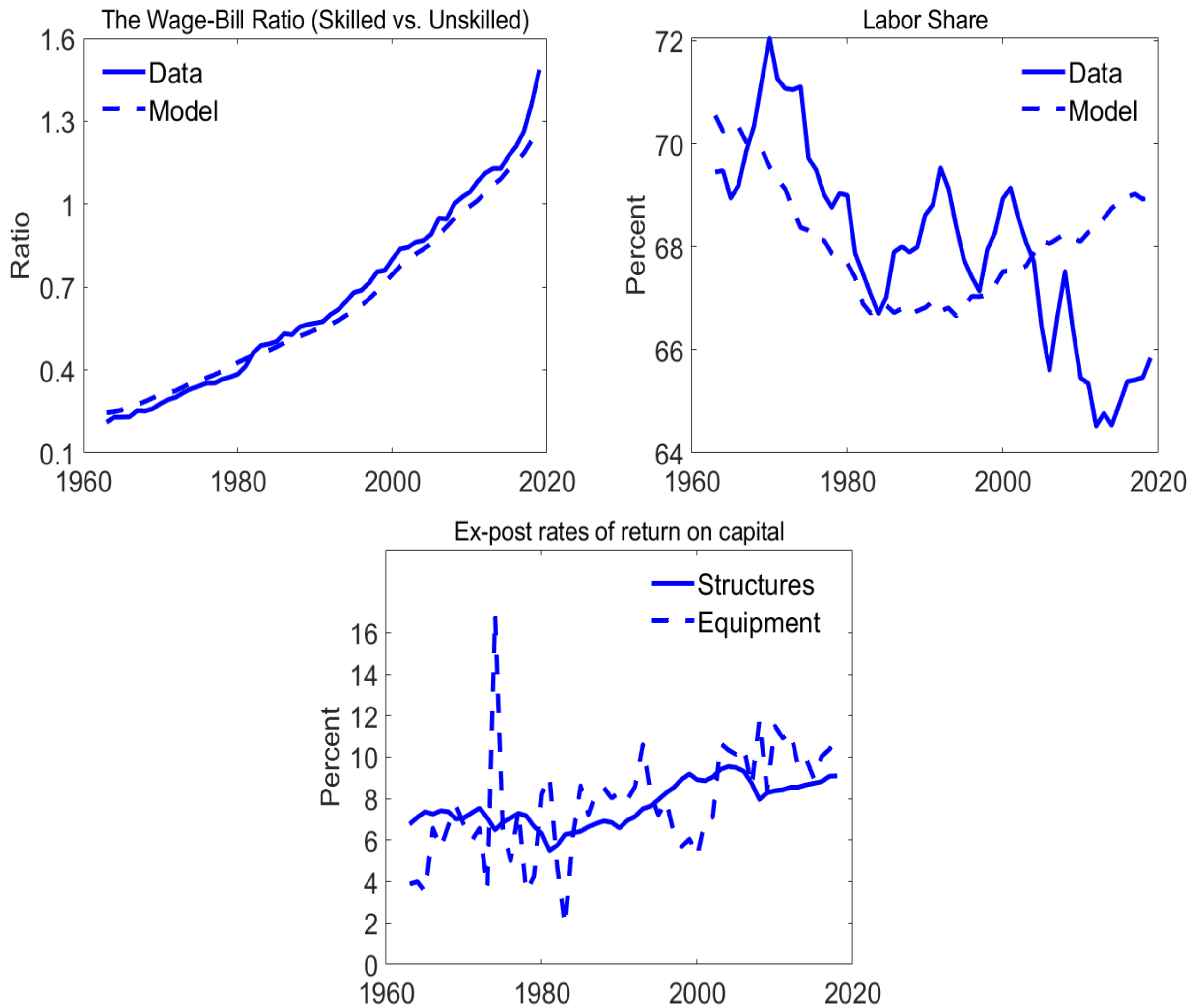

Figure 5.1: Baseline Model's Predictions for Targeted Variables, 1963–2019

Next, we turn to the behavior of the estimated equations in our baseline model that are used as targets. Figure 5.1 presents the model and data equivalents of the ratio of earnings of skilled workers to unskilled workers (the wage-bill ratio) and aggregate labor's share of income, along with the ex-post rates of return on equipment and structures computed from our model. The model statistics are generated by setting the i.i.d. shocks to labor quality to zero at every t, meaning the fluctuations in the model's predictions are entirely due to changes in observable inputs. First, the predictions of the estimated baseline model are broadly in line with the data. The model is able to capture the behavior of the wage-bill

[26]The short-run elasticity estimate we obtained using differenced data is consistent with Polgreen and Silos (2009), who report strong complementarity between equipment capital and energy, and with the short run estimate of Hassler et al. (2021), who present close to perfect complementarity between energy and a composite of aggregate capital and labor.

ratio. It is broadly consistent with the declining labor's share of income, despite being a bit smoother than the data. Overall, our model is consistent with the U.S. labor market trends. Second, the model's predictions for capital variables are also reasonable. For example, our estimates for the ex-post returns are in line with Marx et al. (2021), reporting an increasing return on U.S. productive capital from around 6 percent in the early 1980s to around 12 percent in post-2015. Note that the rate of return is more volatile for equipment than that of structures because of unexpected changes in the relative price of equipment.

Now, we move to the model predictions for the variables not directly targeted in the estimation: the ratio of energy price to skilled wage and the income share of energy. The former ratio is of interest because the relationship between energy and skilled labor affects the course of the energy share, as discussed in Subsection 3.1. Driven entirely by the changes in observed factor quantities, our model successfully mimics the sharp decline in the ratio of energy price to skilled wage until the mid-1970s (Figure 5.2, left panel). It also captures the subsequent rise until the early 1980s. Although it fails to generate the large drop in the early 1980s, it captures the overall secular decline since the 1980s despite not directly targeting the ratio of energy price to skilled wage. As shown in the right panel of Figure 5.2, even without imposing a Cobb-Douglas relationship between equipment capital and energy use, the model successfully captures the relatively stable long-run trend of the energy share. However, it fails to capture the large short-run swings in the energy share.

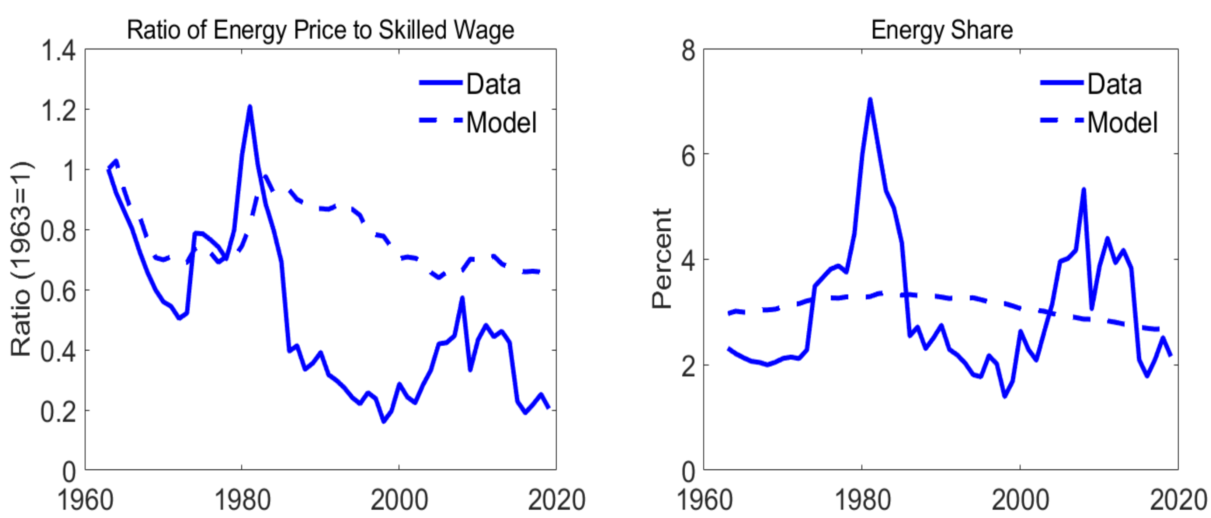

Figure 5.2: Baseline Model's Predictions for Not Directly Targeted Variables, 1963–2019

The income share of energy is a primary object of interest in this paper. One of our main goals is to understand the factors and channels driving its movements. In fact, the ability to construct a historical decomposition of these forces and gain further insight into the behavior of the energy share is a reason behind our choice of a framework with four other factors of production. Recall that in Subsection 3.1, we decompose the growth of the energy share into three components, defined as the capital-energy substitutability effect, the energy-skill complementarity effect, and the skilled labor share effect. Based on this decomposition, we reconstruct how these three channels have affected the income share of energy from 1963 to 2019. The results are presented in the left panel of Figure 5.3 on a logarithmic scale, where the sum of the three components gives the log of the model-implied energy share shown by the solid black line.

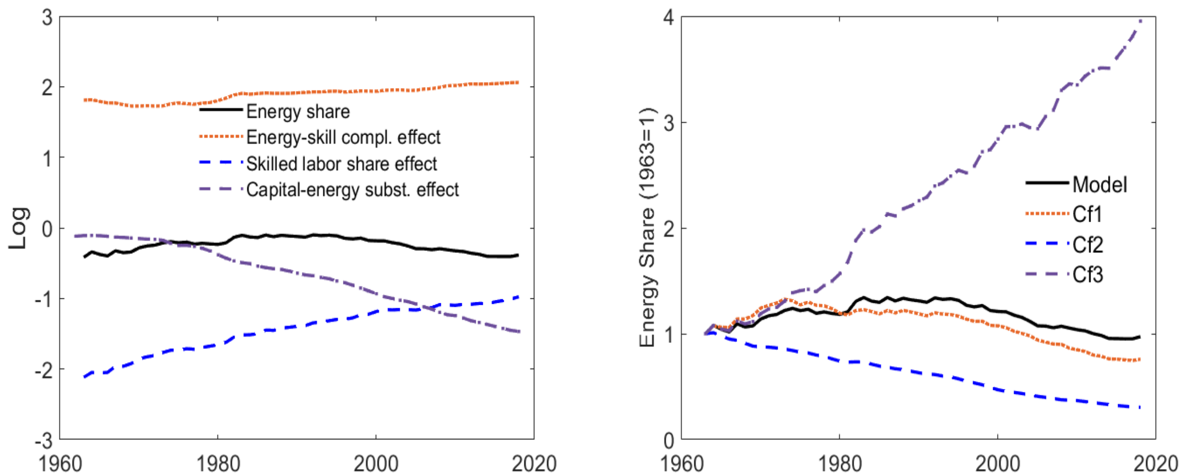

Figure 5.3: Historical Decomposition of the Model-Implied Income Share of Energy (left panel) and Counterfactual Experiments Shutting the Three Mechanisms One by One (right panel), 1963–2019

Note: In the right panel, the solid black line shows the baseline model's prediction for the income share of energy using actual data for all factor inputs. The first counterfactual (Cf1) shows the model's prediction under the assumption that energy and skilled labor grow at the same rate. The second counterfactual (Cf2) shows the model's prediction when the income share of skilled labor remains unchanged at its 1963 level. The third counterfactual (Cf3) shows the model's prediction when $\nu = \rho$ or equipment capital and energy grow at the same rate.

In Figure 5.3, the dotted orange line shows that the energy-skill complementarity effect exerts a positive effect on the energy share throughout the sample, because the skilled labor input grew faster than the energy input and these two factors are complementary. However, this channel is relatively stable, meaning it plays only a modest role in driving the long-run movements of the energy share. Meanwhile, the other two channels seem to have larger and offsetting effects on the energy share. On the one hand, given the secular trend rise in the income share of skilled labor, the energy share tends to increase (the skilled labor share effect, dashed blue line). On the other hand, given that the substitutability between energy and equipment capital is larger than that between capital-energy services and skilled labor ($\nu > \rho$) and that equipment capital and energy are absolute substitutes ($\nu > 0$), the enormous equipment-specific technological progress, coupled with the rise in the income share of equipment capital, depresses the income share of energy (capital-energy substitutability effect, dashed-dotted purple line). Although these two effects seem to largely offset each other, making the long-run trend of the energy share look relatively stable, the capital-energy substitutability effect overall appears to dominate.

To further assess the importance of these channels in the evolution of the income share of energy, we conduct counterfactual exercises by shutting them off one by one. The right panel of Figure 5.3 presents the results. In the first counterfactual (Cf1), we assume that energy and skilled labor grow at the same rate (dotted orange line, shutting off the energy-skill complementarity effect). This channel appears to have been the least important one, as the resulting energy share trend is quite similar to the one the baseline model predicts. In the second counterfactual (Cf2), we assume that the income share of skilled labor remains unchanged at its 1963 level (dashed blue line, shutting off the skilled labor share effect). In this way, we can predict how the energy share would evolve if we did not experience the secular decline in the aggregate labor share, which is partly attributed to the change in the composition of the labor force in favor of skilled labor (see, for example, Orak (2017) and Eden and Gaggl (2019)). This counterfactual suggests that without the rise in the income share of skilled labor, the income share of energy would fall to about one-fourth of its 1963 level. Finally, for the third counterfactual (Cf3), one could either assume $\nu = \rho$ or assume equipment capital and energy grow at the same rate (dashed-dotted purple line, shutting off the capital-energy substitutability effect). Without this effect, the income share of energy would have risen to more than four times its value in the early 1960s, mostly mimicking the rise in the income share of skilled labor. This implies that the enormous rise in the stock of equipment capital has prevented a larger share of U.S. income from being directed to energy use. With a less extreme assumption, the Cf3 experiment suggests that a deceleration in equipment-specific technological progress could lead energy share to rise, everything else being equal.

To summarize, we show that with plausible differences in substitution elasticities, changes in observed factor inputs can explain the historical trend in the income share of energy from 1963 to 2019. Capital-energy substitutability and the share of skilled labor are important in driving the historical trend in the energy share, but capital-energy substitutability seems particularly important. Finally, our model is also consistent with other important characteristics of the U.S. economy.[27]

[27] It is worth noting that our baseline specification assumes Hicks-neutral technical change and allows for skill-specific efficiency in line with the skill premium literature. However, we do not model energy efficiency

5.1 Capital-Energy Substitution and Energy-Saving Technical Change

Supply-side models typically capture medium-term fluctuations in the data. So short-run fluctuations understandably pose a challenge. Notably, the large short-run swings in the income share of energy appear to be primarily driven by the changes in energy prices, as shown in Figure 2.1. In this subsection, we relax the constant elasticity assumption and explore whether dynamic capital-energy substitution can help explain these short-run fluctuations in the energy share. It is possible that higher energy prices may incentivize energy-saving technical change, which may partly reflect omitted shorter-term changes in equipment capital-energy substitutability.

We begin this investigation by exploring patents data. The left panel of Figure 5.4 presents low-carbon innovations as measured by their share of new internationally cited patents along with the real (fossil) energy price. As can be seen, the two series are strongly, positively correlated, providing evidence for innovations induced by energy price shocks.[28] The first two oil shocks and then the 2000s rise in energy demand growth, largely driven by China, spurred waves of innovations, from solar photovoltaic (PV) and wind turbines to hydraulic fracturing transforming global energy markets so that natural gas could replace coal.[29]

The right panel of Figure 5.4 presents how energy prices and the share of global low-carbon patents relate to our parameter governing the elasticity of substitution between equipment capital and energy, ν, where we allow for time variation. We account for time-varying substitution elasticity by running expanding-window OLS regressions to estimate ν, starting from the 1963–1972 period—marked by significant energy price fluctuations due to the first oil shock—up to 2019. This approach avoids relying on a constant long-term estimate derived from six decades of data for the early periods of our study, which experienced

in the baseline. To explore the implications of this assumption, we considered an alternative version of the model where we defined a stochastic efficiency process for the energy input, similar to those defined for skilled and unskilled labor inputs (equation 4.2). In this alternative case, we estimated a greater degree of substitutability between energy input (measured in efficiency units) and equipment capital compared to the baseline, but the overall model fit remained largely unchanged. Specifically, this alternative framework suggests an annual growth rate for energy efficiency of around 5.5 percent, which seems higher than existing estimates, such as those reported by Hassler et al. (2021) for the 1973-2018 period. Moreover, the fits of the variables of interest do not improve meaningfully when we incorporate energy-saving technological growth into our baseline framework. For instance, the normalized root mean square error for the energy share variable improves only slightly from 0.454 to 0.439. Given these findings, we maintain our focus on explaining changes in the energy share through the lens of substitution, particularly capital-energy substitutability, which may serve as a proxy for unobserved and omitted variables including energy efficiency, and help account for changes in the variables using observable factors.

[28] In a related work, Nunes and Catalao-Lopes (2020) examine the impact of oil prices on patent applications for alternative energy sources.

[29] Acemoglu et al. (2023) examine the long-run innovation and climate consequences of shale gas boom.

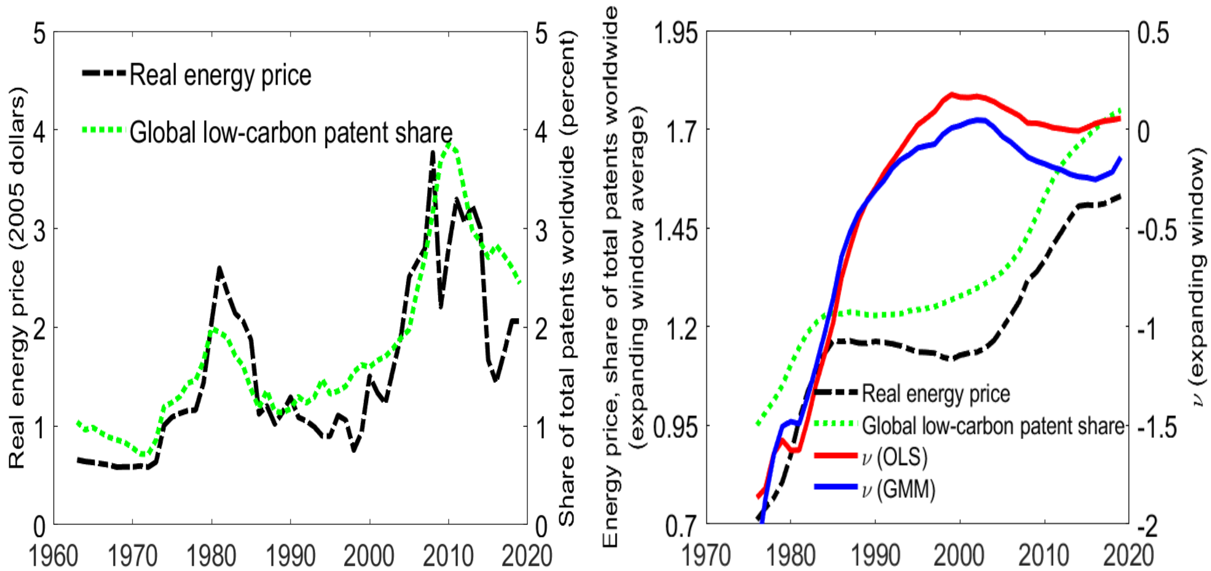

Figure 5.4: Global Share of Low-Carbon Patents and Real Energy Price (left panel) and Expanding-Window Estimates of ν, Expanding-Window Averages of Real Energy Price, and Global Share of Low-Carbon Patents (right panel)

Note: Patent data are for high-value patents defined as those filed in two or more countries. Low-carbon (or clean) technologies include decarbonization technologies related to buildings, including housing and appliances; capture, storage, sequestration, or disposal of greenhouse gas emissions; reduction of greenhouse gas emissions related to energy generation; decarbonization technologies related to transportation; and system integration technologies related to power network operation. Data are from the European Patent Office (EPO), PATSTAT Worldwide Patent Database. Clean technology patent classification is based on EPO and the United Nations Environment Programme (2014). The values of ν, the parameter governing the elasticity of substitution between equipment capital and energy, are estimated by expanding-window (1) OLS regressions of equation 4.3 (the solid red line) and (2) estimates of the production function 5.1 using the GMM methodology with four targets, including the energy share (the solid blue line). The initial period covers 1963–1972. Each subsequent period adds one more year to the previous period.

significant price changes and rapid technological advances in the energy sector.[30] Alternatively, we estimated ν using GMM for the same expanding-window periods.[31] Solid red and solid blue lines in the right panel of Figure 5.4 present the resulting estimates of ν.

Both solid lines show that substitutability between equipment capital and energy has increased significantly since the mid-1970s, which coincides with higher average energy prices as well as higher average clean patent shares relative to the mid-1970s as presented by the

[30]For robustness, we also explored a rolling-window estimation for ν, which utilized shorter-term elasticity measures throughout the entire study period. This alternative approach further improved the model-implied energy share fit, reducing the normalized root mean square error to just 0.138 and capturing almost all short-term fluctuations observed in the data. However, we opted against this method due to a deterioration in the model fit for the other variables, such as the skill premium.

[31]The GMM estimation targets included the no-arbitrage condition, the wage-bill ratio, the labor share, and the energy share.

dashed-dotted black line and the dashed green line, respectively. This finding is consistent with Popp (2002), who found a strong positive relationship between energy prices and energy-efficient innovation using patent data, with a relatively quick response time. Overall, these results are in line with our interpretation that energy-saving technological progress—due to rising energy prices—may partly reflect omitted shorter-term changes in capital-energy substitutability.

Table 5.2: Estimates of Key Model Parameters with Time-Varying ν's

Model	Methodology	σ	ρ	α	ν
With time-varying ν's	OLS+SPMLE	0.426	−0.372	0.091	–
With time-varying ν's	GMM	0.496	−0.351	0.092	–
Baseline	OLS+SPMLE	0.431	−0.363	0.094	0.056

Next, we use those time-varying ν estimates to examine our model's fit. We use the estimates presented by the solid red line in the right panel of Figure 5.4, along with their corresponding ξ estimates, in our SPMLE methodology to estimate the rest of the parameters. We also estimate our model with GMM for robustness. Table 5.2 presents the resulting parameter estimates. It shows that the other two substitution elasticities (σ, ρ) and the share of structures capital (α) are similar to those in our baseline considering a constant ν and ξ for the entire 1963–2019 period. As a result, the model's fit for the labor market variables with time-varying ν's is similar to those reported for the baseline model (Figure A.3 in the Appendix), meaning the model maintains its consistency with major U.S. labor market trends.

More remarkably, our model now better captures the short-run movements in the income share of energy. Figure 5.5 shows that we can account for the short-run swings in the energy share, particularly in the earlier periods of the study. That is, when we take into account time-varying capital-energy substitution, changes in observed quantities can explain the variation in U.S. (fossil) energy dependence (as measured by its income share of energy) to a greater extent. All in all, it appears that firms are able to adopt their technologies in response to changes in energy prices despite energy prices being generally more volatile than other input prices.[32]

In the next subsection, we will incorporate alternative (non-fossil) energy sources into our baseline framework and explore the extent to which the economy could move closer to achieving climate-related objectives in the long-run.

[32]This price volatility is partly because factors such as global geopolitics, not only demand or supply conditions, also affect energy prices.

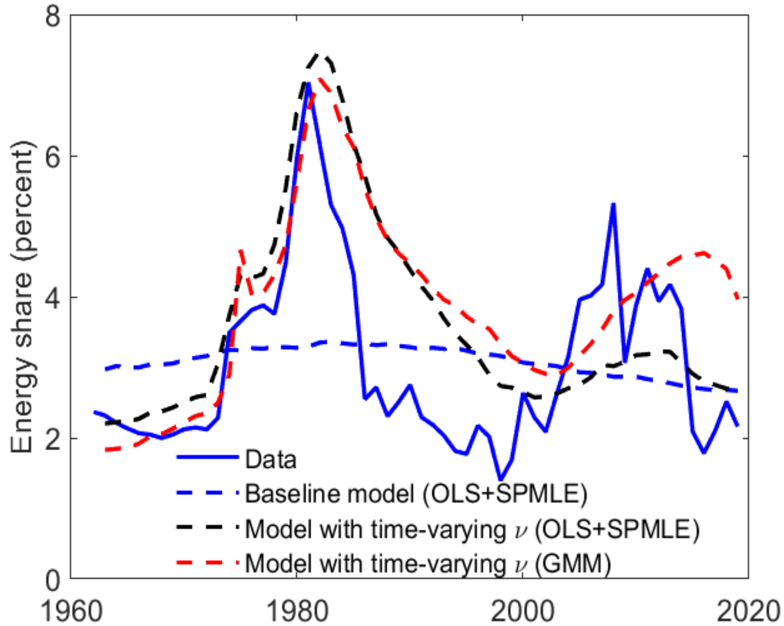

Figure 5.5: The Model's Predictions for the Energy Share with Time-Varying ν's versus the Baseline, 1963–2019

5.2 Pursuing and Achieving Long-Term Climate Change Mitigation Goals

In our baseline model, we focus on fossil energy because of its historical significance as the primary source of energy consumption in the U.S. (as illustrated in Figure 5.6, left panel). This historical perspective underscores the vital role fossil energy plays in understanding U.S. energy dependence. Considering that emissions from fossil fuels stand as the predominant driver of global warming, it becomes imperative to take into account substitution possibilities between alternative (non-fossil) energy sources and fossil energy in the assessment of climate-related objectives. Consequently, we present a version of the model featuring two energy types.

More specifically, we assume an energy composite consisting of two types of energy, fossil and non-fossil, such that:

$$Y_t \;\; = \;\; A_t K_{s,t}^{\alpha}\Big[\mu L_{u,t}^{\sigma} + (1-\mu)\big(\lambda[\xi K_{eq,t}^{\nu} + (1-\xi)[\theta E_{nf,t}^{\phi} + (1-\theta)E_{f,t}^{\phi}]^{\frac{\nu}{\phi}}]^{\frac{\rho}{\nu}} + (1-\lambda)L_{s,t}^{\rho}\big)^{\frac{\sigma}{\rho}}\Big]^{\frac{1-\alpha}{\sigma}},$$

where $E_{nf,t}$ and $E_{f,t}$ are non-fossil and fossil energy inputs, respectively, and $\frac{1}{1-\phi}$ is the elasticity of substitution between the two energy input types.

To estimate this modified version of the model, we require data on the income share of

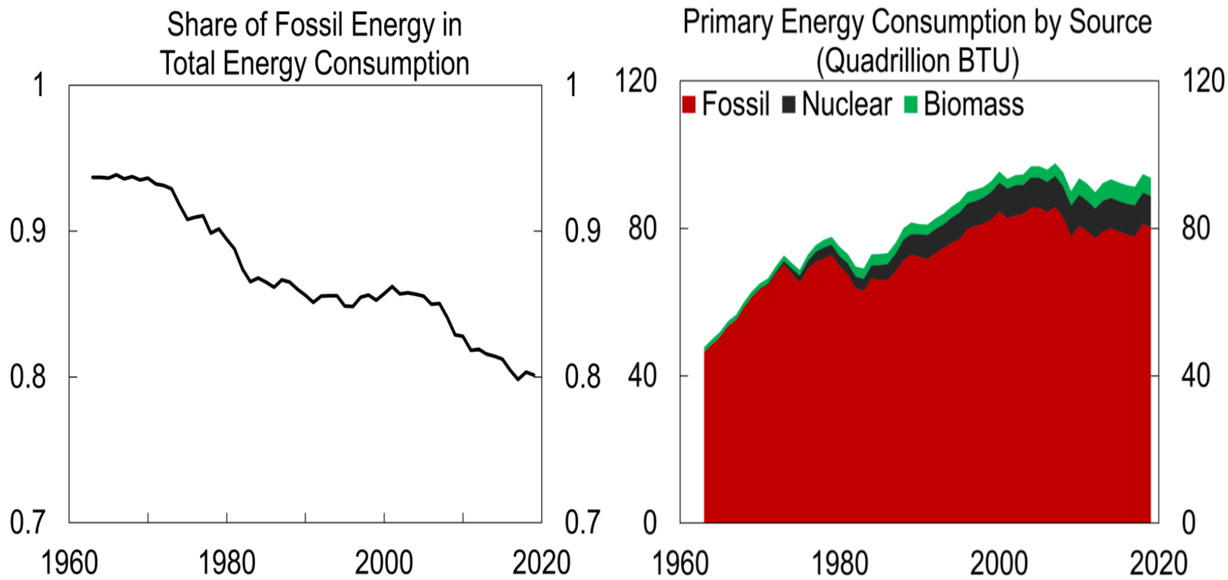

Figure 5.6: Fossil Energy Share in Total Primary Energy Consumption in the U.S., and Fossil and Non-Fossil Energy Use, 1963–2019

non-fossil energy. It is crucial to acknowledge that comprehensive and consistent historical data on both the price and quantity of non-fossil energy, particularly solar and wind, over extended periods is notably scarce. Consequently, we rely on historical primary energy expenditure data from the Energy Information Administration (EIA), which is available from 1970 and includes only nuclear and biomass among non-fossil energy sources. Thus, we utilize biomass and nuclear as proxies for non-fossil energy in our extended model estimation covering the period from 1970 to 2019, which can be considered a long-term elasticity.[33]

First, we find that fossil and non-fossil energy sources are substitutable, with an elasticity of substitution of 1.4.[34] This parameter is scarcely estimated in the literature. One exception is Papageorgiou et al. (2017), who provide evidence that the elasticity of substitution between clean and dirty energy inputs significantly exceeds unity.[35] Acemoglu et al. (2023) consider 1.85 as a summary of their findings for use in macroeconomic models. Our elasticity estimate can be considered an economy-wide measure. It falls within a reasonable range reported in existing literature, underscoring the robustness and relevance of our model despite the

[33]We use Table ET1 to obtain the income share of non-fossil energy (measured as nominal expenditures on biomass and nuclear as a share of output, which is nominal GDP minus the value of energy use outside of domestic production).

[34]In this version of the model, the substitution elasticity between energy composite and equipment capital is 1.16, slightly higher than the baseline model's 1.06. Details on the estimation and model results are available upon request.

[35]Papageorgiou et al. (2017) use sectoral data from 26 countries spanning 1995-2009, providing targeted insights rather than a comprehensive economy-wide estimate. Their sector-specific analyses yield an elasticity of around 2 for the electricity sector and values between 1.5 and 3 for non-electricity sectors.

necessary abstractions due to data limitations.

Second, incorporating non-fossil energy into the model has minimal effect on our baseline outcomes, as the estimates of other substitution elasticities and model fit results remain predominantly consistent. This outcome is to be expected, given the relatively small contribution of non-fossil energy to the total U.S. income, particularly when compared to fossil energy and other production factors. With this extended model, we are now equipped to delve into long-term policy inquiries.

Upon rejoining the Paris Agreement in 2021, the U.S. set forth a new target: Lower emissions by 50 to 52 percent below 2005 levels by 2030.[36] As part of its long-term strategy, the U.S. has embraced an objective of achieving net-zero emissions no later than 2050.[37] These objectives prompt an intriguing thought experiment: To what extent can the U.S. economy gravitate toward the realization of these environmental targets?

The reduction of CO2 emissions hinges on diminishing carbon intensity. When formulating environmental objectives, we establish a clear linkage between the carbon intensity of U.S. output and the (fossil) energy intensity of output, employing a straightforward decomposition: $\frac{CO2}{Y} = \frac{CO2}{E}\frac{E}{Y}$, where $CO2$ is energy-related carbon emissions, Y is GDP, and E is fossil energy use. Figure 5.7 plots each component of the decomposition between 1969 and 2019, with data normalized to 1969 values. Notably, over this period, the carbon intensity of output fell by approximately 70 percent (solid black line), a decrease closely mirrored by the decline in the (fossil) energy intensity of output (dashed red line). Concurrently, the carbon intensity of energy displayed a relative stability (dotted red line). As a pivotal factor influencing carbon emissions, our attention zeroes in on the implications of our model for the energy intensity of output, particularly in the context of targets grounded in the globally embraced Paris Agreement. In essence, leveraging our framework, we examine the extent to which the economy can substantially reduce its fossil energy intensity—roughly by 50 percent below 2005 levels by 2030—and further probe how far this intensity can be driven down through the year 2050.

Such an experiment requires assumptions about price trajectories, though the long-term energy price outlook is notably uncertain. Furthermore, a comprehensive measure of carbon-free energy costs remains absent, as previously mentioned. Nevertheless, recent evidence strongly indicates a decline in the real price of carbon-free energy (see, for example, Gilling-

[36] This target covers all sectors. When emissions from land use, land use change, and forestry are excluded, the recalibrated goal stands at a $44-47$ percent reduction from 2005 levels by 2030 according to the Climate Action Tracker (CAT), an independent scientific project that tracks government climate action and measures it against the Paris Agreement.

[37] Achieving net-zero emissions means an economy either emits no greenhouse gas emissions or offsets its emissions through actions such as tree planting or employing technologies that can capture carbon before it is released into the air.

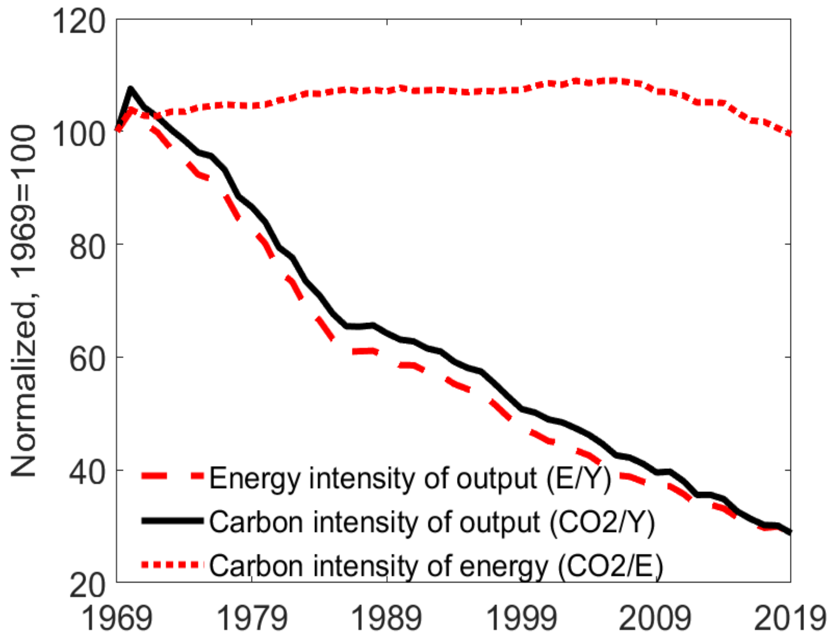

Figure 5.7: U.S. Carbon Intensity Accounting

Note: $CO2$ data come from Our World in Data.

ham and Stock (2018)). For post-2019 pricing of non-fossil energy, we adopt the National Renewable Energy Laboratory's (NREL) 2021 Annual Technology Baseline (ATB) projections, specifically focused on the levelized cost of nuclear energy up to 2050. Turning to post-2019 pricing of fossil energy, we rely on the EIA's Annual Energy Outlook 2023 (AEO 2023) projections for prices and consumption and adopt the methodology we used earlier to construct fossil prices.[38] Dashed lines in the left panel of Figure 5.8 plot these price paths, suggesting a declining trend for non-fossil prices and an increasing trend for fossil prices. Higher fossil energy prices in the long run are in line with mitigation policies, such as carbon taxes, raising tax-inclusive prices of energy.

For the remaining variables, we assume the following: The stock of structures capital and total factor productivity, A_t, will maintain their post-Global Financial Crisis (post-GFC) annual average growth rates of 0.6 percent and 0.4 percent, respectively, through 2050. Labor supplies and skill abundance (the share of skilled employees in total employment)

[38]NREL's 2021 ATB offers an engineering-based bottom-up projection of technology-specific levelized energy costs spanning 2019 to 2050. It's worth noting that using utility-scale PV prices yielded comparable results. The AEO 2023 explores long-term energy trends in the U.S. We consider AEO 2023 *reference case* in our experiment. To determine real energy input prices, we adjust the projected nominal fossil and non-fossil energy prices using the GDP deflator. Based on realized data up to 2022, we assume a 4 percent rise in the GDP deflator for 2023, followed by annual increments of 2 percent in subsequent years.

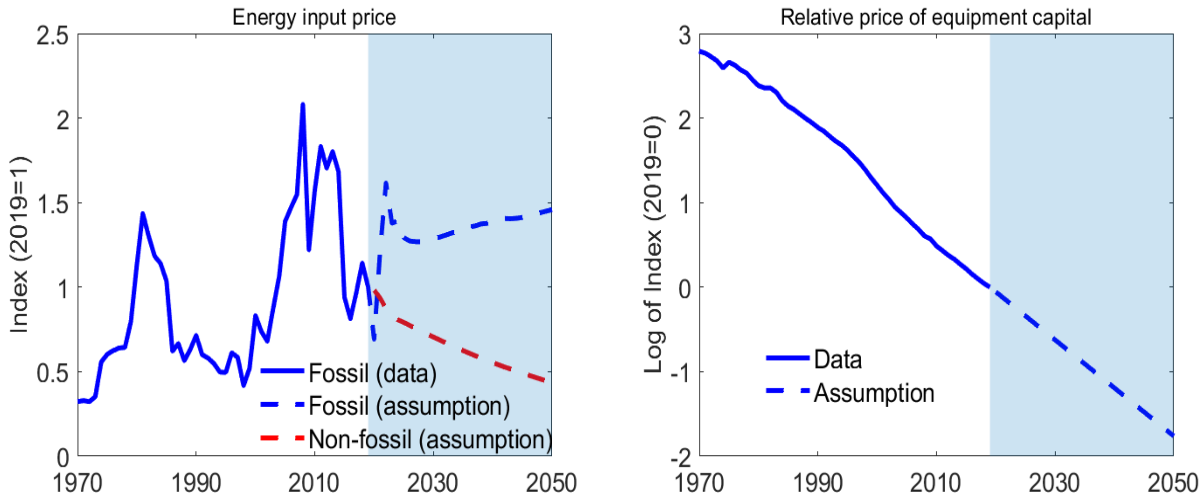

Figure 5.8: Assumed Price Paths

Note: In the left panel, the solid blue line depicts actual real fossil energy prices. The dashed blue line represents the fossil price trajectory derived from the EIA's AEO 2023 projections up to 2050, while the dashed red line illustrates the real cost of nuclear energy using NREL's 2021 ATB projections within the same time frame. In the right panel, the solid blue line displays equipment capital's relative price from the data, while the dashed blue line portrays the assumed price path for the post-2019 period as detailed in the text.

will grow at their post-GFC rates, implying the ratio of skilled labor to unskilled labor will increase by an annual rate of 2.9 percent. An increase in skilled labor supply aligns well with an evolving energy landscape, as low-carbon energy sectors may require workers with skills necessary for these jobs (see, for example, Vona et al. (2018)), and the successful integration of new technologies is likely contingent upon the presence of suitable skill sets within the labor force. Additionally, we assume that the relative price of equipment capital will continue its decline at the post-GFC average growth rate of 5.5 percent through 2050 (as shown by the dashed line in the right panel of Figure 5.8). With these assumptions in place, we utilize our extended model to jointly project fossil energy use, non-fossil energy use, and equipment capital through 2050. This experiment incorporates the substitution elasticities estimated over the 1970–2019 period, thereby representing long-run elasticities. The results are presented in Figure 5.9, where the left panel illustrates the income share of (fossil) energy and the right panel shows the fossil energy intensity of output—defined as the ratio of fossil energy use to real GDP, expressed in units of 1,000 British thermal units (Btu) per chained (2012) dollar.

Under the aforementioned assumptions, our model implies that the U.S. income share of (fossil) energy declines to below 2 percent by 2050, representing a notable departure from its historical 50-year average of 3.2 percent. This decline can be attributed to both

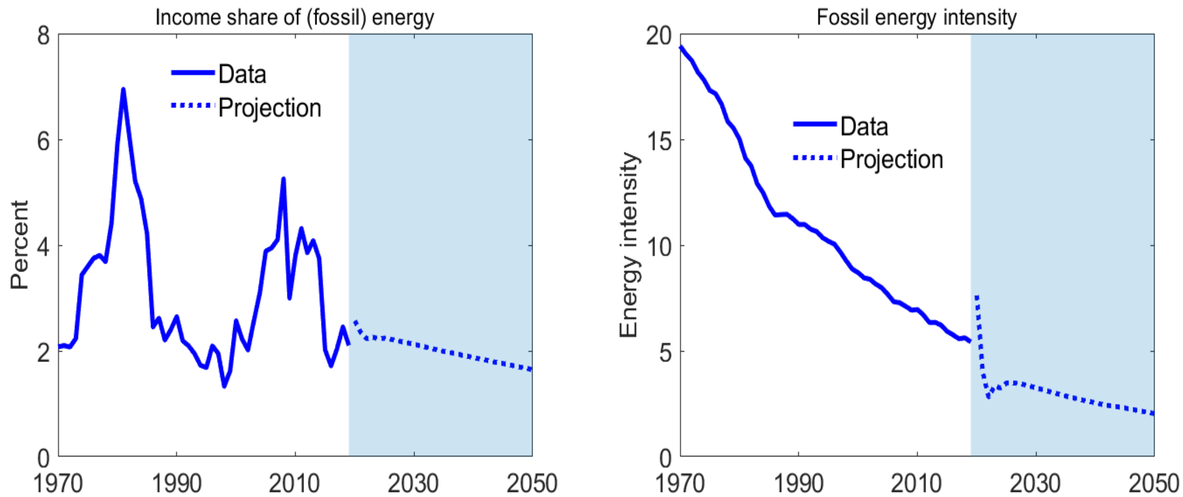

Figure 5.9: Model Predictions for the Income Share of Fossil Energy (left) and Fossil Energy Intensity (right)

Note: Shaded areas show the extended model projections under the aforementioned assumptions.

shifting energy use to non-fossil alternatives and, more significantly, substituting energy with equipment capital. With respect to intensity, over decades, the fossil energy intensity of U.S. output has steadily declined. This downward trajectory in fossil energy intensity continues through 2050, as shown by the dotted blue line in the right panel of Figure 5.9. Our model predicts a decline of more than 50 percent in U.S. fossil energy intensity below its 2005 level by 2030, suggesting alignment with the Paris Agreement objectives.[39] By 2050, this intensity hovers at approximately 2.2 thousand Btu per chained dollar, representing more than a halving from its 2019 level. Note that this projected decline in fossil energy intensity by 2050 is predominantly driven by the decline in the relative price of equipment capital (see Figure A.4). Striving for near-zero intensity appears to necessitate at least another decade, extending our projection past 2050.[40] In essence, our analysis underscores the feasibility of achieving the 2030 target, but reaching the 2050 goal seems to demand additional steps, such as further acceleration in equipment-specific technological advancements.[41]

[39] The COVID-19 pandemic, the Russian invasion of Ukraine, and the ongoing energy transition have catalyzed shifts in the global energy landscape, propelling large swings in energy prices over the 2020–2022 period (as evidenced by the spike in the dotted blue line in the left panel of Figure 5.8). Our model parameters are estimated using data through 2019. However, the energy price projections incorporate actual data up to 2023. This means the predicted spike in fossil energy intensity over 2020–2022 is driven partly by the substantial swings in observed energy prices.

[40] In this exercise, we assume energy prices will grow at their 2041-2050 average rate through 2070 while holding assumptions about other variables the same.

[41] Regarding the labor-related aspects of the economy (not shown), our model predicts around a 2 percentage point increase in the labor share and a notable reduction in the skill premium. This shift can be attributed, in part, to the skilled labor supply surpassing demand resulting from capital deepening (under

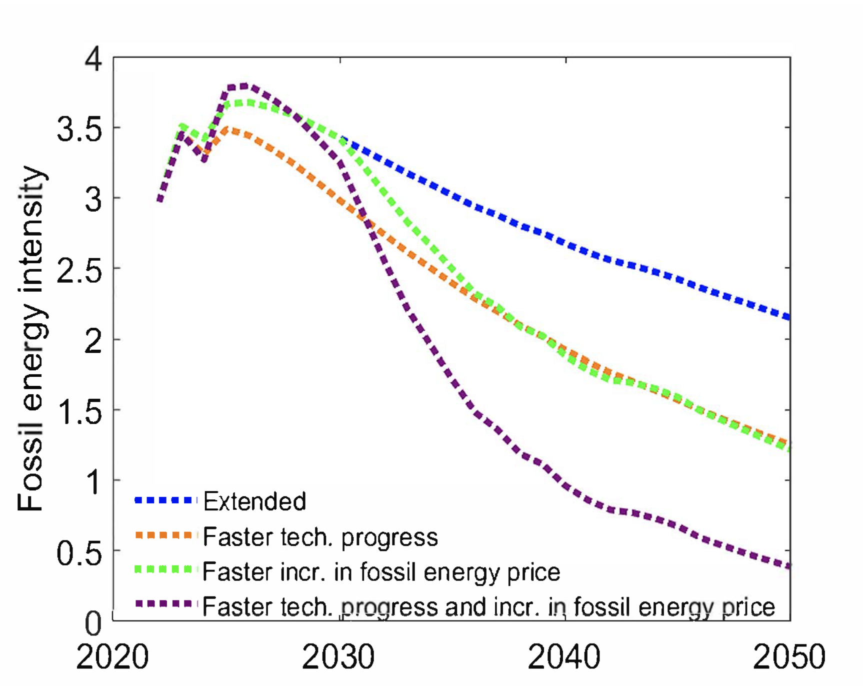

Figure 5.10: Path to Near-Zero Fossil Energy Intensity

Note: The dotted blue line shows our extended model's prediction for fossil energy intensity based on the aforementioned assumptions (presented in Figure 5.8). The orange dotted orange line presents the counterfactual projection when the pace of equipment-specific technological change is assumed to double relative to the extended model's assumption. The dotted green line shows fossil energy intensity under the assumption of fossil energy prices increasing five-fold faster than in the extended model. The dotted purple line combines these two counterfactuals.

Within this context, we conduct a counterfactual experiment to examine potential paths to achieving near-zero fossil energy intensity. We explore two scenarios: one assumes a faster rate of equipment-specific technological progress, and the other posits a more rapid increase in fossil energy prices than previously assumed in Figure 5.8. Figure 5.10 illustrates the outcomes of these scenarios with the dotted orange and dotted green lines, respectively, and compares them to the extended model's projection from Figure 5.9 (dotted blue line). If the decline in the relative price of equipment capital doubles relative to the prior assumption, all else being equal, fossil energy intensity would drop an additional 42 percent by 2050—down to around 1.2 Btu per chained dollar, as indicated by the dotted orange line. A comparable reduction, shown by the dotted green line, occurs if the fossil energy price increase is quintupled.[42] When we combine these two scenarios—accelerated technological progress and significantly higher fossil energy prices (purple dotted line)—fossil energy intensity falls to near-zero levels, 0.39 Btu per chained dollar by 2050. Thus, meeting the 2050 objective may require an even greater boost in equipment-specific technological progress and a more substantial reduction in fossil energy use triggered by steeper price increases.

The substitution possibilities between energy and equipment capital, as well as between fossil and non-fossil energy emerge as important forces driving our results. The potential for more affordable and superior equipment capital assumes a crucial role in diminishing the economy's fossil energy intensity over the coming decades. Consider this: If the relative price of equipment capital had remained steady up until the year 2050, all else being equal, our results would have indicated a relatively stable fossil energy intensity trajectory. Thus, a compelling avenue to curbing the economy's fossil energy intensity and, subsequently, its carbon intensity may lie in bolstering the equipment capital stock. This seems to align with the aspirations set forth by the U.S.' IRA, which seeks historic investments to address climate change. By advancing the accessibility and quality of equipment capital, one can catalyze energy-efficient technological advancements, fostering a domain of increased substitution opportunities between equipment capital and fossil energy. Furthermore, a complementary strategy involves reallocating resources toward augmenting the abundance of non-fossil energy sources and driving down their costs.

In light of our findings in this section, it is beneficial for policymakers to consider integrating the dynamic interchangeability between energy and capital equipment when designing climate policies. This integration can help facilitate a more precise gauge of energy intensity in the shorter term, empowering the design of effective long-term environmental strategies.

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our assumptions).

[42] We assume a five-fold increase in the fossil energy price to achieve a decline in fossil energy intensity comparable to that resulting from doubling the decrease in the relative price of equipment capital.

The pursuit of enhanced and more affordable equipment capital is an instrumental means to achieve environmental targets. When policymakers devise strategies to mitigate U.S. carbon intensity, it is also crucial to factor in the interaction between fossil and non-fossil energy.

6 Conclusion

In this paper, we present a simple, explicit economic mechanism for understanding an economy's dependence on fossil energy and for interpreting energy-saving technical change. We estimate an aggregate production function with two types of capital, two types of labor, and (fossil and non-fossil) energy, using different methods and disaggregated U.S. data over the past six decades. We find that equipment capital-energy substitutability and skilled labor share are important factors in understanding the historical trend in U.S. fossil energy dependence, with the former being particularly significant. By considering time-varying capital-energy substitutability, we show that changes in observed factor inputs alone can largely account for the short-run movements in the income share of energy over the past six decades—an important insight complementing work on directed technical change and energy reliance.

Through the lens of our theory, we then make projections regarding climate-related objectives, suggesting the feasibility of achieving certain targets. Achieving the long-run goal of net-zero emissions, however, may require more than our current assumptions, such as an acceleration in equipment-specific technological advancements or significantly cheaper non-fossil energy sources. Our findings suggest that the development of more affordable and advanced capital equipment can play a crucial role in reducing the economy's carbon intensity over the coming decades.

Finally, our analysis underscores the importance of considering disaggregated inputs in environmental macroeconomics and provides essential substitution elasticities that enhance our understanding of directed technical change and its relation to climate change. This analysis can be applied to other countries and can be extended and integrated into broader assessment models, such as integrated assessment models.

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<u>**For Online Publication**</u>

A Appendix

A.1 Data Construction

A.1.1 Construction of Energy-Related Series

We construct the energy variables following Hassler et al. (2021), using data from the EIA, as follows.

Our data covering 1949 to 2019 suggest that the average price for crude oil in 2005 dollars per Btu is 3.75 times as high as the coal price, while the average price for natural gas in 2005 dollars per Btu is 1.57 as high as the coal price. So we compute fossil energy use as $E_t = E_t^c + 3.75E_t^o + 1.57E_t^g$, where E_t^c, E_t^o, and E_t^g stand for coal consumption, crude oil consumption (excluding biofuels), and natural gas consumption (excluding supplemental gaseous fuels) in million Btu, respectively. These series are available for the 1949–2019 period from Table 1.3: "Primary Energy Consumption by Source," *Monthly Energy Review*.

We obtain the fossil energy price variable as $P_t = (P^c E_t^c + P^o E_o^c + P^g E_t^g)/E_t$. For that purpose, we first create individual price series P^c, P^o, and P^g of coal, crude oil, and natural gas, measured in dollars per million Btu. For the crude oil price, we use "Domestic Crude Oil First Purchase Prices (dollars per barrel)," which can be found at `https://www.eia.gov/dnav/pet/pet_pri_dfp1_k_a.htm`. We divide this series by "Crude Oil Production Heat Content (million Btu per barrel)" to create a series of the crude oil price in dollars per million Btu. The Crude Oil Production Heat Content series is available in Table A2: "Approximate Heat Content of Petroleum Production, Imports, and Exports," *Monthly Energy Review*. For the natural gas price, we use two different series because of discontinuity of a series. We use "U.S. Natural Gas Wellhead Price (dollars per thousand cubic feet)" from 1949 to 2012 and "U.S. Natural Gas Electric Power Price (dollars per thousand cubic feet)" from 2013 to 2019. The former can be found at `https://www.eia.gov/dnav/ng/hist/n9190us3a.htm`, and the latter can be found at `https://www.eia.gov/dnav/ng/hist/n3045us3a.htm`. We alter the unit of the combined series to dollars per cubic foot and then divide it by "Natural Gas Production, Marketed Heat Content (million Btu per cubic foot)" to construct the natural gas price in dollars per million Btu. The Natural Gas Production Heat Content series is available in Table A4: "Approximate Heat Content of Natural Gas," *Monthly Energy Review*. For the coal price, we use "Nominal Coal Price, Total" for the 1949-2019 period available in Table ES-4: "Nominal Coal Prices," *Annual Coal Report*. We divide the coal price series by "Coal Production Heat Content (million Btu per short ton)" to construct a coal price series in dollars per million Btu. After constructing individual price series in dollars per million Btu, we deflate them with the GDP deflator to express the price series in thousands of 2005 dollars per million Btu.

We calculate the output measure as $Y = GDP - (net\, exports\, of\, fossil\, fuel)$. For GDP, we use real GDP in 2005 dollars. We use data from Table 1.4c: "Primary Energy Net Imports by Source (million Btu)" in *Monthly Energy Review* and multiply net exports by price to express the net export in dollars. Then, we sum the net export values of three fuel types to construct the Fossil Fuel Net Exports series. Here, we use the GDP deflator to express the series in 2005 dollars. We then construct our fossil energy share as $E_t P_t / Y_t$, where Y_t is measured net of the net export of fossil fuel, as mentioned.

A.1.2 Construction of Labor Inputs and Wages

We follow Krusell et al. (2000) and Ohanian et al. (2023) in constructing the labor inputs and wage rates. Here, we summarize our steps briefly and refer interested readers to those papers for more details.

Labor inputs and wage rates are constructed using the individual–level data from the Current Population Surveys (CPS) from 1963 to 2019. Also similar to Domeij and Ljungqvist (2019), we have both a labor input sample and wage sample. In the former, we drop those younger than 16 or older than 70, those reported as unpaid family workers or in the military, those who were not in the labor force in the previous year, and those who have missing qualifications, such as their educational attainment. In the latter, we also drop the self-employed and agents who reported working less than full time (that is, 40 weeks a year and 35 hours a week). Finally, observations with allocated income, those with hourly wages below half of the minimum federal wage rate, and those with weekly pay less than \$62 in 1980 dollars are all dropped.

Individuals are first divided into 264 groups based on their age (16–20, 21–25, 26–30, 31–35, 36–40, 41–45, 46–50, 51–55, 56–60, 61–65, and 66–70); sex (male or female); race (white, black, others); and educational attainment (less than high school, high school, some college, and a college degree and/or more). We also record each individual's employment status, class, weekly hours worked (usual hours worked per week for the post-1975 period and weeks worked last year before that), weeks worked a year before, and total wage and income a year before. Using this information and CPS personal supplement weights, we calculate income and total hours worked for each individual for each year in the sample. In doing so, we do not make any adjustments for top codes, because, as Ohanian et al. (2023) report, results are not affected much by the treatment of top-coded incomes.

Once we have the total income and hours worked for each individual, we calculate their wage rates simply by dividing their total income to total hours worked. We then aggregate these individual hours to calculate total hours for each of the 264 groups and calculate average wage rates for each group by taking the weighted average of wages of each individual in the relevant group. Finally, these 264 groups are aggregated into two skill categories: skilled and unskilled, based on the educational attainment of each group. We define skilled labor only as those with a college or graduate degree. We use the group wages of 1980 as the weights when aggregating the groups into skilled and unskilled categories.

A.1.3 Construction of the Income Shares of Labor and Equipment Capital

To maintain comparability, we construct gross labor share as described in Krusell et al. (2000). As such, labor share is constructed as *"1 − aggregate capital share,"* where aggregate capital share is the ratio of the sum of net interest and miscellaneous payments, rental income of persons with capital consumption adjustment, corporate profits with inventory valuation and capital consumption adjustments, and depreciation to the difference between gross domestic income and proprietors' income from the BEA's NIPA Tables 1.10 and 1.17.5.

We then subtract energy share from aggregate capital share to obtain the sum of income shares of equipment capital and structures, which we call non-energy capital share.

To construct a series for the income share of equipment capital, we first assign a constant share of income to structures capital, consistent with the Cobb–Douglas technology we assumed for it—that is, we take the α estimate of Ohanian et al. (2023) as given. Then, we obtain *equipment capital share* as the remaining part of the non-energy capital share, which is used in estimating energy-related parameters ν and ξ employing equation 4.4.

A.2 Additional Results

Model Fit for Specifications I and II

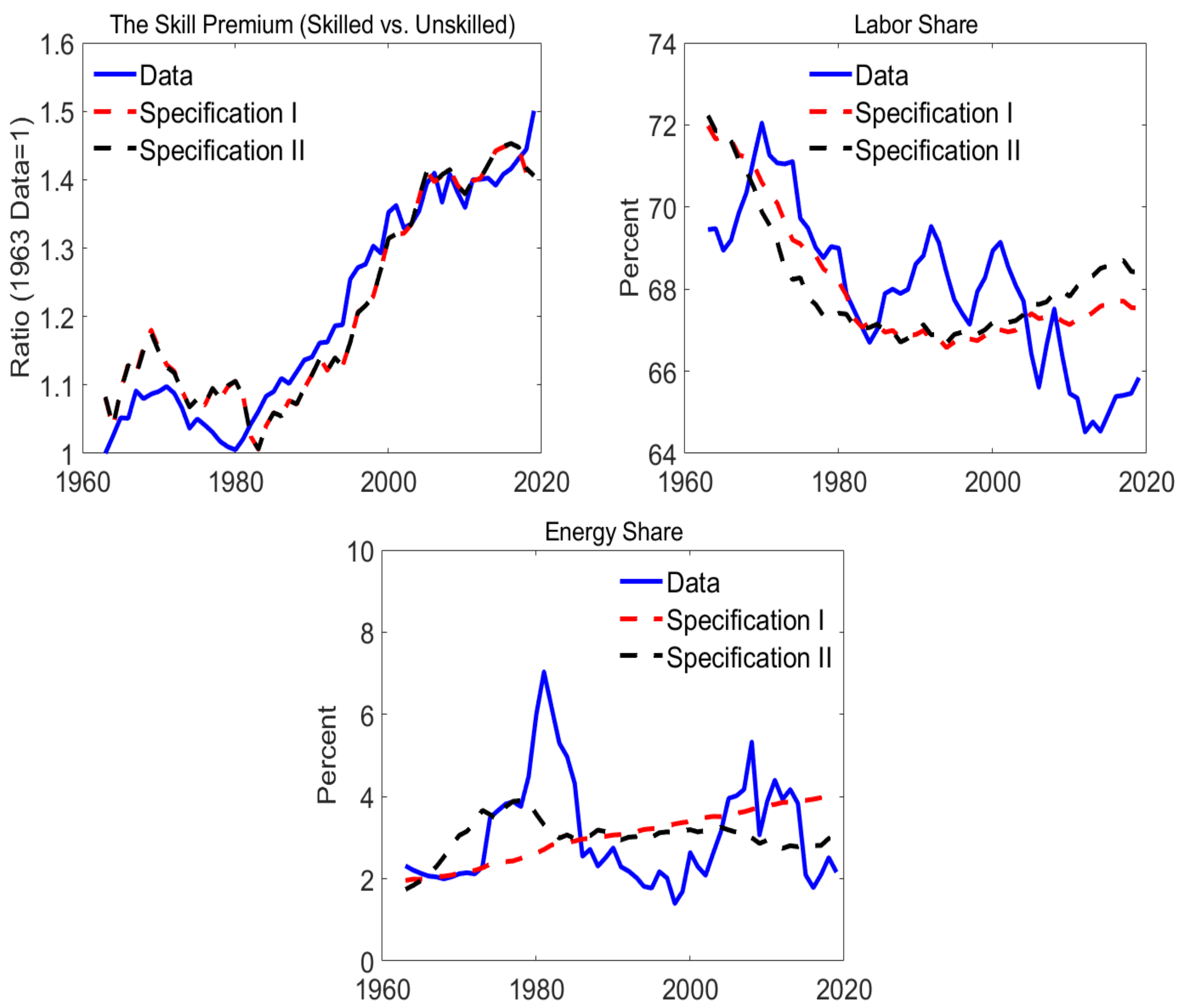

Figure A.1: Model Fit for Specifications I and II

Note: This figure shows the model fits for two production technology specifications presented in the top two rows of Table 3.1.

Baseline Model versus Alternative Model with Energy Share as the Target

In the baseline model, we consider three targets: wage-bill-ratio, no-arbitrage condition, and aggregate labor share. In an alternative scenario, we replace aggregate labor share with the income share of energy, and keep the other two targets the same—that is,

1. **Baseline**: no-arbitrage, wage-bill ratio, labor share
2. **Alternative**: no-arbitrage, wage-bill ratio, energy share

We estimate the parameters of the alternative model using SPMLE, similar to the baseline model, for consistency. Note that ν is estimated using OLS in both cases, resulting in 0.0555. The estimated parameters for the alternative case are presented along with the baseline values in Table A.1.

Table A.1: Parameters Estimated for the 1963–2019 Period

	σ	ρ	α
Baseline	0.431	−0.363	0.094
Alternative	0.344	−0.547	0.095

The alternative model's predictions are presented in Figure A.2. As seen in the figure, the model fails to capture the level and the decline of the labor share when the energy share replaces the labor share as the third target.

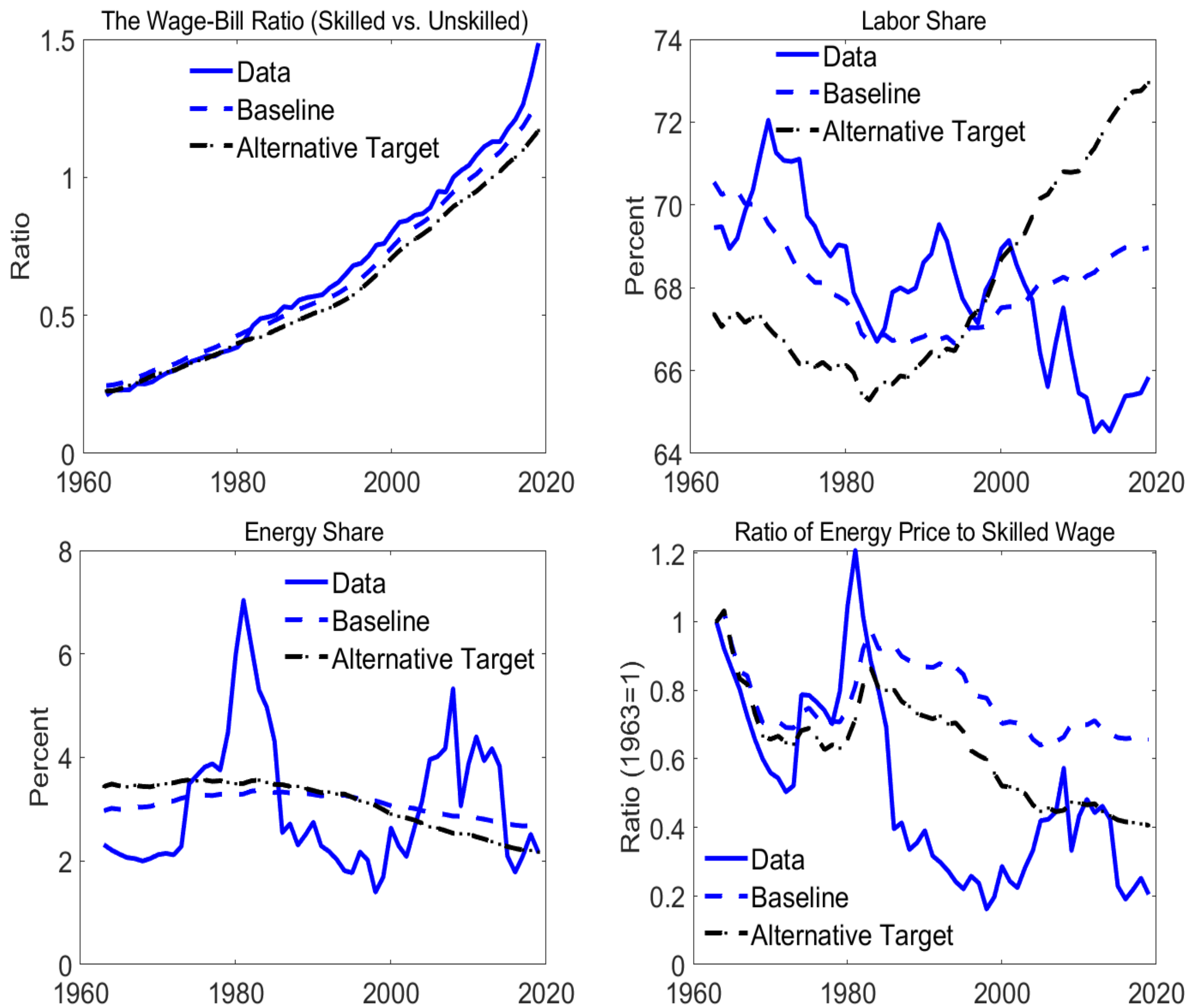

Figure A.2: Baseline Model versus Alternative Model

Model Fit with Time-Varying ν's

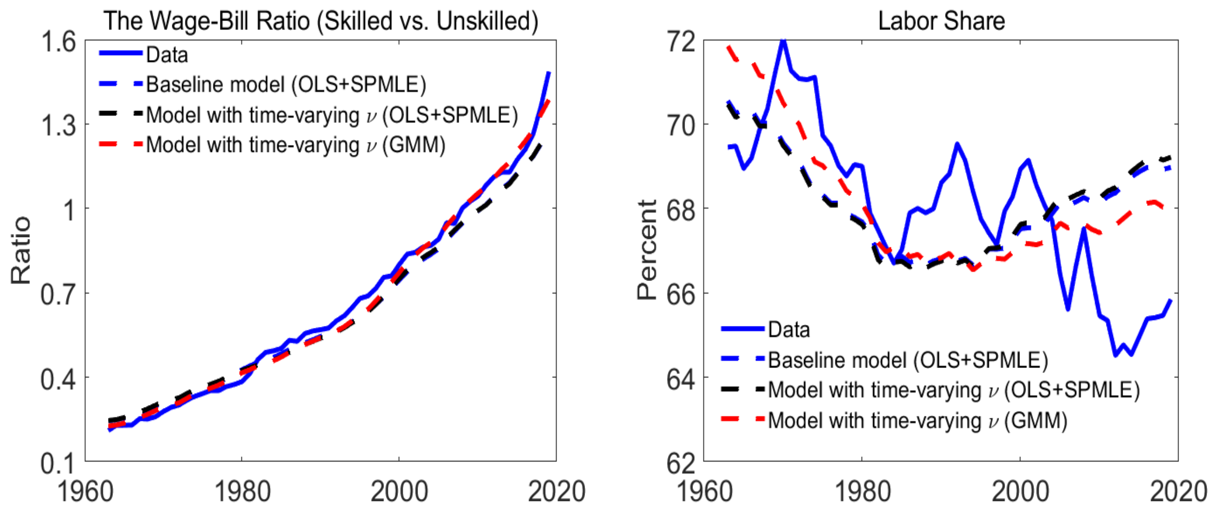

Figure A.3: The Model's Predictions with Time-Varying ν's for Labor Market Variables, 1963–2019

Roles of the Relative Price of Equipment Capital versus Energy Prices in Lowering Fossil Energy Intensity

In this counterfactual exercise, we assess the relative importance of equipment-specific technological progress and energy prices in driving the predicted decline in fossil energy intensity through 2050, as shown by the dotted blue line in Figure A.4. If we keep our assumed path for the relative price of equipment capital unchanged but hold energy prices constant at their 2019 level, the model projects fossil energy intensity to decline to 2.31 BTU per chained dollar (the dotted black line, counterfactual 1). This implies that the equipment-specific technological progress channel alone can account for almost 90 percent of the decline in fossil energy intensity from 2023 to 2050. Conversely, if we maintain the energy price assumptions as they are, but keep the relative price of equipment capital unchanged at its 2019 level, fossil energy intensity falls only to 3.14 BTU per chained dollar by 2050 (the dotted red line, counterfactual 2). This exercise suggests that the projected decline in fossil energy intensity is predominantly driven by the decline in the relative price of equipment capital.

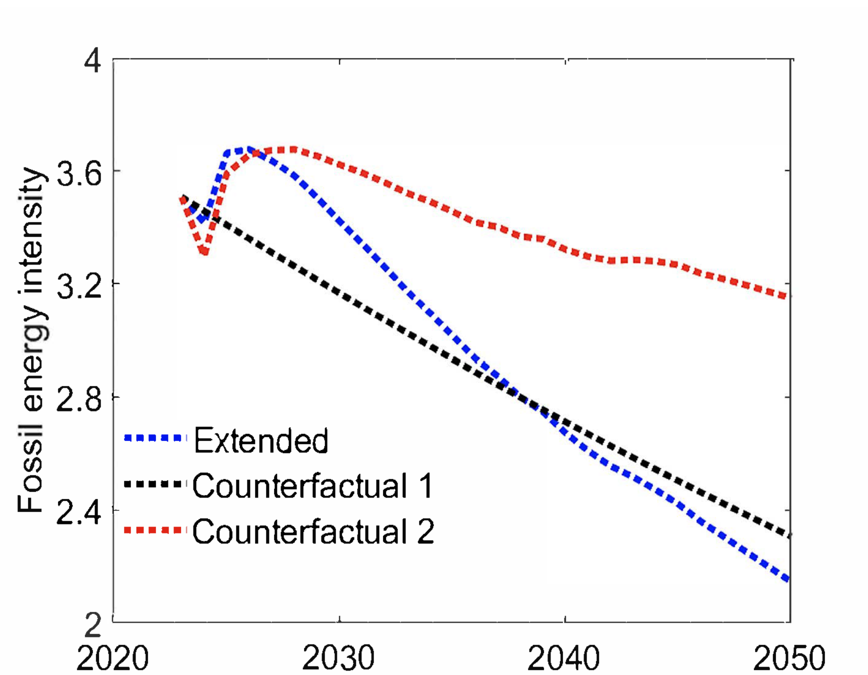

Figure A.4: Roles of the Relative Price of Equipment Capital versus Energy Prices