Climate change mitigation and economic development

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

Anthropogenic climate change, caused by greenhouse gas (GHG) emissions, will have negative if not catastrophic consequences for the livelihoods of many across the globe. With the Paris Agreement in 2015, most countries have pledged to reduce territorial GHG emissions. Per-capita emission levels are highest in today's rich countries, and many have started reducing their emissions. Current middle-income economies such as China, Ghana, India or Indonesia have experienced rapid economic, population, and emission growth in recent years, and today's poor countries are projected to be responsible for the lion's share of growth in energy demand and emissions in the coming decades. As of 2019, middle-income countries were responsible for over half of global GHG emissions (own claculations based on Olivier and Peters, 2020). While the implementation of climate policies in middle-income countries is crucial for global mitigation efforts, the same is difficult to defend for low-income countries due to justified growth ambitions and very low historical and current emission levels.

Besides switching to renewable energy sources for electricity generation, carbon pricing – either through taxes or trading schemes – as well as fossil fuel subsidy removal are arguably the most important mitigation policy tools available. These policies increase energy prices at least in the short term, thus incurring costs that may harm sustainable development goals. People and firms adapted their behaviour to low and often subsidized fossil energy. Many firms rely on generators powered by cheap diesel, while large parts of the population rely on cheap transportation and buy LPG cookstoves due to subsidized fuel prices. Clean cooking fuel adoption objectives may be hampered by taxing the fossil fuel LPG – the only viable clean cooking fuel in many regions of the world. Rising energy prices come with negative welfare consequences for households that may directly threaten poverty reduction efforts. Further, potential competitiveness losses of firms can dampen economic development prospects.

The trade-off between economic growth and poverty reduction, on the one hand, and per-capita emissions, on the other, is illustrated in Figure 1.1 for selected middle-income countries during the past 30 years. Economic development has always been associated with both an increase in per-capita emissions and a decrease in poverty rates, although considerable country-level heterogeneity exists. For instance, China's and Thailand's growth have been associated with steep rises in per-capita emissions (and steep declines in poverty rates), while India's, Indonesia's, and Ghana's emission trajectories are much flatter. South African and Mexican growth rates and per-capita emissions have been relatively stagnant in the past 30 years, but these countries achieved considerable reductions in poverty rates.

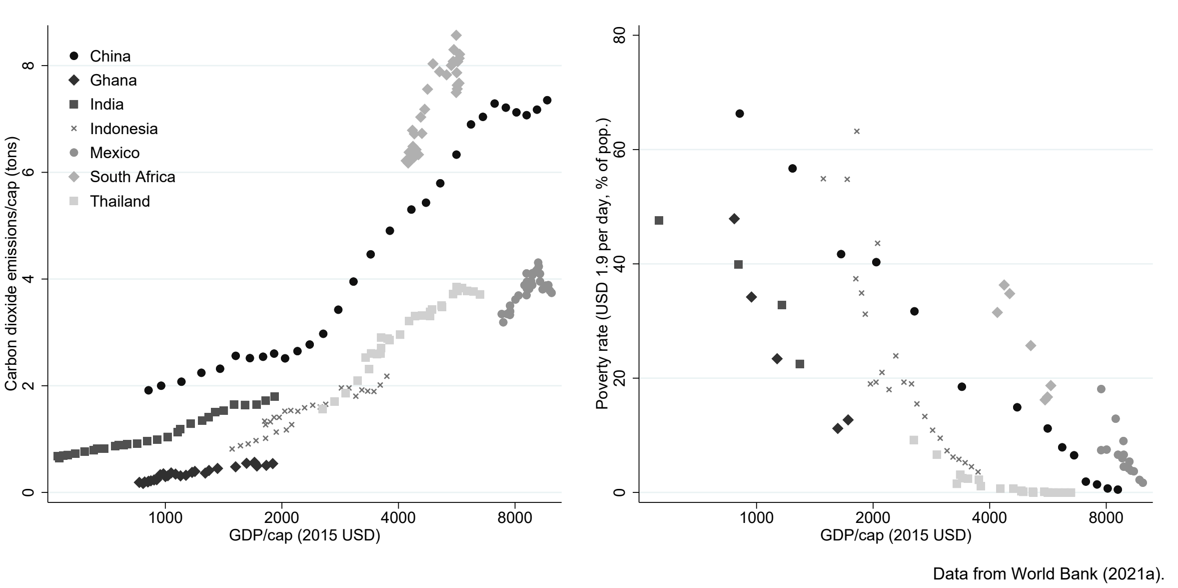


Figure 1.1: Relationship between economic growth, emissions and poverty reduction in selected middle-income countries (1990–2018)

The trade-offs between climate policy and economic development may explain why only few middle-income countries (and no low-income country) have implemented carbon pricing to date. Those countries that have implemented carbon pricing have done so at very low price levels. The removal of fossil fuel subsidies, labelled as "second-best" climate policy for developing countries, has been more frequent. In addition to public welfare and economic growth concerns, the implementation of policies raising energy prices is frequently met with public protests – be it in China, Ecuador, France, Kazakhstan, Kenya or Mexico. These incidences are likely related to in some cases considerable short-term costs of such policies, which are clearly important from a political economy perspective, irrespective of long-term gains. Policy design needs to take into account these costs in order to avoid adverse consequences and to increase public acceptance. For instance, well-designed social transfer schemes can in theory compensate for welfare losses among the poorer population, and reforms can be phased in gradually to avoid sudden price shocks.

This dissertation investigates the impact of rising energy prices, caused by different policies, on different segments of society in two lower-middle-income countries – Ghana and Indonesia – and an upper-middle income country, that is, Mexico. The analyses shed light on the short-term impacts of an increase in energy prices on the performance of small firms in Mexico and on large manufacturing firms in Indonesia, on household welfare impacts and consumption-based GHG emission reduction potential of carbon taxes in Mexico, and on the impact of fossil fuel subsidy removal on clean cooking fuel objectives in Ghana. These analyses hence provide evidence on the effects of climate policies in developing countries and their immediate trade-offs with sustainable development goals. This empirical basis can inform decision makers on how to design complementary policies aimed at mitigating adverse impacts for sustainable development, and thus may also contribute to a more rapid introduction of mitigation policies.

1.1 Anthropogenic climate change and global mitigation efforts

Anthropogenic climate change has already warmed Earth's surface temperature by around 1.1°C in the past decade compared to the pre-industrial era (IPCC, 2021). If humankind continues to increase GHG emissions, temperatures will likely rise by between 3.6–4.4°C by 2100. The risk of catastrophic consequences of global temperature increases and the likelihood of extreme events rises with every additional increment of global warming. Immediate threats include sea level rise and extreme weather events like heatwaves, heavy precipitation, and droughts, and impacts of climate change have already materialized around the globe. So-called *tipping elements*, such as thawing of the permafrost or the Gulf Stream switching off, are becoming more likely to be activated, which could lead to irreversible changes in the Earth's system and to uncontrollable temperature increases (Steffen et al., 2018). Climate change is also directly threatening the survival of a large number of plant and animal species (IPBES, 2019), one of nine identified planetary boundaries of a "safe operating space for global societal development" (Steffen et al., 2015; Rockström et al., 2009).[1] Further, with increasing CO_2 emissions, carbon sinks – at land an in the ocean – become less effective, so that future emissions will have a larger impact on global surface temperature than past emissions. It is therefore paramount to reduce global GHG emissions as soon as possible and as fast as possible in order to avoid as many of the consequences of anthropogenic climate change as possible.

With the Paris Agreement in 2015, the international community committed itself to keep the global surface temperature increase to well below 2°C. Despite this commitment, total GHG emissions have grown between 2009–2018 by an average of about 1.2 percent annually to reach roughly 58 $GtCO_2eq$ in 2018 (Minx et al., 2021). While the recent emission growth rate is lower compared to the growth rate of 2.4 percent annually between 2000–2009, it still points

[1] Climate change is one planetary boundary, with the other eight being biosphere integrity, land-system change, ocean identification, atmospheric aerosol loading, freshwater use, biogeochemical flows, ozone depletion, and (so far unknown) novel entities.

in the wrong direction given the large emission reductions needed to reach climate goals. In case global emissions remain constant, the carbon budget for reaching 1.5 degrees warming (with a likelihood of at least a two-thirds) will be exhausted by 2028, and the carbon budget for reaching 2 degrees warming will be exhausted by 2046.[2] In 2020, carbon dioxide emissions have decreased by about 5 percent compared to 2019 due to COVID-19 confinement measures (Andrew and Peters, 2021). However, emissions are projected to increase substantially in 2021 due to a rebound in coal and oil use (IEA, 2021b). Just before the Conference of the Parties in 2021 in Glasgow (COP26), nationally determined contributions (NDCs) were expected to limit global warming to 2.7°C by the end of this century (UNEP, 2021). Factoring in pledges for carbon neutrality, current policy goals are projected to lead to an increase of 2.1°C by 2100, while currently implemented policies are projected to lead to an increase of 2.7°C (Climate Action Tracker, 2021). At COP26, world leaders have promised to update their countries' NDCs in order to conform to the goal of keeping global surface temperature increase "well below" 2°C.

Carbon dioxide remains the dominant greenhouse gas at about 66 percent of total GHG emissions in 2018 due to the sheer magnitude of emissions (Minx et al., 2021). Mitigation efforts often focus on investments in renewable energy technology in the electricity sector, since almost two-thirds of total GHG emissions (including emission estimates of land-use change) stem from electricity and heat production (Olivier and Peters, 2020). Currently, the major emitters of CO_2 are China (31 percent of the world's total), the USA (14 percent), India (7 percent), Russia (5 percent), Japan (3 percent), Iran (2 percent), and Germany (2 percent), while Indonesia is the 10th largest, Mexico the 16th largest, and Ghana the 93th largest emitter (Andrew and Peters, 2021). In per-capita terms, oil-rich countries in the Middle East, small states such as Brunei or Luxemburg, as well as large industrialized countries like Australia and the USA emit the most. While the USA and the EU – but also Mexico – have managed to reduce total GHG emissions in recent years, emerging economies like China and India, but also Indonesia and Ghana continue to increase emissions, with the exception of 2020. Ghana, for instance, more than doubled total CO_2 emissions between 1990 and 2019, while Indonesia almost tripled them in the same period.

In 2021, the first year after the start of the COVID-19 pandemic, energy demand has rebounded and is projected to grow further through 2022 (IEA, 2021a). This growing global energy demand especially in the Asia Pacific region outpaces the deployment of low-carbon electricity generation, leading to increased emissions of the energy sector in 2021 and 2022, even though energy intensity of electricity generation (CO_2 per kWh) continues to decrease slightly in all world regions (IEA, 2021a). Population growth will add to the growing energy demand in emerging and developing countries, especially in sub-Sahara Africa (SSA) (Ayompe

[2]MCC carbon clock based on IPCC (2021), available at `https://www.mcc-berlin.net/en/research/co2-budget.html`.

et al., 2020), that currently has low levels of total energy consumption (the African continent is responsible for roughly six percent of the world's total), but which will be home to the majority of the additional two billion people added to the world population by 2050. Hence, due to economic and population growth, most of the additional global final energy demand will come from low- and middle-income countries in the next decades, while energy demand in high-income countries is projected to remain stable or decline (IEA, 2021b).

Decarbonization of the energy sector is essential for mitigation efforts. Renewable sources like wind and solar power are variable electricity sources that need to be combined with dispatchable power sources in order to ensure stability of the electricity grid. Dispatchable sources include fossil fuels, nuclear power plants, hydropower, biogas plants, geothermal plants, and energy storage. The International Energy Agency for instance advocates the construction of nuclear power plants "where acceptable" while phasing out coal for electricity generation as fast as possible to lower emission intensity of energy use (IEA, 2021b). Likewise, the IEA urges for the promotion of electric vehicle use to substitute fossil fuels in the transportation sector. A second component of mitigation strategies are energy efficiency improvements, such that energy intensity (energy per unit of GDP) decreases. These can be incentivized through carbon pricing as well as targeted subsidies. Third, cutting methane emissions from fossil fuel extraction operations is crucial to limit GHG emissions in the near-term. Lastly, innovation plays an important role, as many net-zero pledges hinge on technologies that are yet to be fully developed, such as carbon capture and storage. Any policy aimed at mitigating climate change will have to additionally consider impacts on society as well as unintended impacts on other planetary boundaries (Sterner et al., 2019).

Carbon pricing, either through carbon taxes or emission trading systems, corrects the market price of fossil fuels by internalizing (some of) the damages of GHG emissions, thereby discouraging wasteful consumption and incentivising energy efficiency improvements through technology adoption and innovation, and many studies have verified its effectiveness for emission abatement in industrialized countries (e.g. Gugler et al., 2021; Nordhaus, 2019). Another important effect of carbon pricing is the creation of a price wedge between producer and consumer prices, because low producer prices discourage production of fossil fuels (Sterner et al., 2019). In contrast to targeted regulation, carbon pricing also allows flexibility in where, when, and how emissions are mitigated, which lowers mitigation costs (Weyant, 2017). Likewise, removal of fossil fuel subsidies – where in place – has been promoted as a viable climate policy for low- and middle-income countries. These key climate change mitigation policies, that is, carbon pricing and fossil fuel subsidy removal, lead to energy price increases.

In the absence of an international price on emissions or carbon border adjustment mechanisms, so-called *carbon leakage* may reduce the effectiveness of national or regional climate policy. Production may shift from regulated jurisdictions to unregulated ones, while lower demand may lead to lower international fossil fuel prices and thus to increased use in regions with no carbon pricing (Naegele and Zaklan, 2019; Zhang and Zhang, 2017). To avoid this, the European Union, for instance, is considering the introduction of a carbon border adjustment mechanism. This would exert pressure on middle-income countries to implement carbon pricing as well in order to avoid competitiveness losses for local firms exporting to the EU, and to reap the fiscal gains of carbon taxes themselves. In sum, this political development makes the introduction of more ambitious carbon pricing in middle-income countries more likely in the coming years.

1.2 Growth ambitions and mitigation policies in developing countries

In the past decades, human development has made tremendous progress. The share of the world population living below the extreme poverty line of USD 1.9/day has decreased from 43 percent in 1981 to 9.3 percent in 2017, thanks in large parts due to poverty reduction in China as well as India, while around 40 percent of the population in SSA still lives in extreme poverty (World Bank, 2021a). This positive development has been made possible by sustained economic growth. However, economic growth has always been associated with an increase in GHG emissions. The emission trajectories of countries like Brazil, China, India, Indonesia, Mexico and Thailand closely follow those of industrialized European countries (Jakob et al., 2014b). There is no precedence of a country becoming rich without extensive use of fossil energy and natural resource exploitation.

Decarbonizing existing energy systems in industrialized and emerging countries is the most important component of international efforts to reach global emission reduction targets. Due to the rapid emission growth in recent years of today's low- and lower-middle income countries and projected population and economic growth, especially in SSA, many scholars have recently discussed the necessity of mitigation policies to avoid "lock-ins" in long-lived fossil-fuel based energy systems in these regions (Goldstone, 2021; Steckel et al., 2020; Mattauch et al., 2015). With China's pledge to stop financing coal power plants abroad (Brant, 2021), the threat of the proliferation of coal-powered electricity generation in SSA seems to have been removed. Recent efforts of rich countries to urge the World Bank to phase out investment in natural gas projects in developing countries (Abnett and Shalal, 2021) seems at odds with the growing energy demand on the continent necessary to reach sustainable development goals (Moss and Ramachandran, 2021). In addition, adaptation to climate change is often prioritized, especially because poor (and hotter) countries are projected to be more vulnerable to climate change impacts than rich ones, for instance through effects on labour productivity or the submergence of coastal cities due to rising sea levels (Dasgupta et al., 2021; Desmet and Rossi-Hansberg, 2021; Kulp and Strauss, 2019; Tol, 2018).

Climate finance lies at the heart of climate change mitigation efforts for low- and middle-income countries. Most nationally determined contributions (NDCs) of developing countries make the implementation of ambitious mitigation policies conditional on financial resource flows, technical assistance, technology transfers, and capacity-building support. Especially in SSA, weak state capacity is an important bottleneck to scaling up investment in the energy sector, and thus capacity building is a top priority (Arezki, 2021). Here, adequate policy design can prevent a *climate finance curse* that may harm development prospects of developing countries (Jakob et al., 2014a). The fact that rich countries have fallen short on their promise to provide 100 billion USD annually in climate finance to developing countries by 2020 – an amount estimated to be only a drop in a bucket compared to the needed trillions to reach the climate goals – does not inspire confidence that the latter will prioritize ambitious mitigation policies without significant increases in finance flows (Timperley, 2021).

Developing countries face important trade-offs between climate change mitigation policies that raise energy prices and other sustainable development goals such as economic growth, poverty eradication (SDG1), equity concerns (SDG10) and energy access (SDG7) (Jakob and Steckel, 2016). The latter includes access to grid electricity as well as decentralized mini-grids in rural areas (Lenz et al., 2017; Grimm et al., 2016; Peters and Sievert, 2016), but also access to clean energy for cooking – including the fossil fuel LPG. Political economy issues due to vested interests of the fossil fuel industry are further barriers for climate action, for example in Indonesia (Ordonez et al., 2021).

For these reasons, the most important policy tool for mitigation efforts – carbon pricing – has not yet been implemented in any low-income and in only few middle-income countries. For instance, Mexico has implemented a tax in 2014 of 3.5 USD per tonne of CO_2 equivalent for specific fuels and end-users (Prat, 2020) and Indonesia scheduled a carbon tax in 2021 of about 2.1 USD (Yulisman, 2021). These taxes are too low to yield a steering effect: The OECD, for instance, has estimated that the needed global price on carbon emissions should be around 136 USD by 2030 in order to reach net zero emissions by 2050 (OECD, 2021). In 2021, only around 22 percent of global GHG emissions were covered by carbon pricing, and the estimated average global carbon price is at 2-3 USD – far below the estimated price for reaching mitigation goals (World Bank, 2021b).

In the absence of ambitious carbon pricing, fossil fuel subsidy removal has been advocated by international organizations as so-called “second-best” climate change mitigation policy for developing countries (Coady et al., 2018; Rentschler and Bazilian, 2017; Jakob et al., 2014b). These subsidies put a high burden on government budgets, incentivize wasteful consumption of fossil fuels and discourage investment in energy efficiency technology and hinder the transition towards low-carbon energy systems. Moreover, in developing countries, they tend to benefit the richer population (Arze del Granado et al., 2012). Globally, the extent of subsidies has declined in recent years due to lower international fossil fuel prices and efforts to reform subsidies, and many countries have implemented reforms, including Ghana and Indonesia, although many countries continue to subsidize fossil fuels – especially coal (Coady et al., 2019).

Despite the caveats of fossil fuel subsidies, their removal often meets public opposition due to the short-term costs they impose, and hence are politically difficult to implement (Coady et al., 2018; Rentschler and Bazilian, 2017). Successful subsidy reforms are characterized by a comprehensive communication strategy, a gradual increase of energy prices, targeted measures to protect the poor, providing suitable substitutes (such as public transportation) and concerted efforts to reform the energy sector (Coady et al., 2018; IMF, 2013). However, energy system transformations can be thwarted by small but powerful interest groups (Arent et al., 2017), and climate legislation is typically weaker where the coal industry is strong (Kim et al., 2015). Many developing countries also continue to subsidize LPG to enhance the transition to modern cooking fuels (Troncoso and da Silva, 2017; Kojima, 2016). Other mitigation options include policies promoting the adoption of energy efficient technologies through e.g. subsidies. However, effective design of such policies in developing countries remains difficult due to limited capacity to raise revenues, poor power quality that limits willingness to pay for new technologies, credit constrained households, and government capacity deficits in many countries (Fowlie and Meeks, 2021).

1.3 Impacts of carbon pricing and higher energy prices in developing countries

Carbon pricing has already been implemented, or is scheduled to be, in middle-income countries like Mexico and Indonesia, and many countries including Ghana and Indonesia have implemented fossil fuel subsidy reforms. These policies have led to rising energy prices, and future mitigation efforts will likely result in further increases. Apart from implementation issues of ambitious climate policy such as insufficient finance flows or political economy issues, adverse impacts on household welfare, inequality, and competitiveness of firms in developing countries are further potential barriers for action. Effective policy design thus demands theoretical guidance and empirical evidence on (potential) impacts of rising energy prices in order to assess feasibility of policies aimed at raising the price of emissions and to identify additional measures aimed at mitigating adverse impacts.

One great concern is that raising energy price may harm competitiveness of domestic industries. Studies on high-income countries have so far only found no or negligible short-term effects of carbon pricing on the international competitiveness of firms (see Venmans et al., 2020, for a recent overview of studies). However, one reason for the small effects are the relatively low carbon prices under the period of investigation. On a positive note, many studies find a positive effect on productivity and innovation, in particular increases in the number of patents (eg. Löschel et al., 2019; Cui et al., 2018; Marin et al., 2017; Calel and Dechezleprêtre, 2016). A recent study on OECD countries finds that rising energy prices have positive employment effects, and suggests that new employment opportunities are created in the abatement technology producing and instalment sectors that compensate for job losses in energy-intensive industries (Hille and Möbius, 2019). To date, only few studies investigate the effects of rising energy prices on firms in developing countries (e.g. Abeberese, 2017; Rentschler and Kornejew, 2017), one important reason being lack of high-quality data on firms in developing countries.

However, it is likely that effects of rising energy prices on firms in developing countries is different compared to those in rich countries. First, most firms are small, informal, operate at low levels of productivity and have only limited capacity to invest in new technology to potentially adapt to e.g. price shocks (Grimm et al., 2012). Second, even large firms differ from their rich-country counterparts. They often have to deal with a poor electricity grid, and hence typically rely on diesel generators for electricity generation (Alby et al., 2012). This will likely affect their reactions to rising energy prices, which has not been investigated to date. Potential impacts on labor demand may also have repercussions for household welfare: Higher energy prices may lead to reductions in wages, or worse, dismissals due to competitiveness losses and subsequent contraction of production. The creation of *green* jobs may compensate for job losses in *dirty* sectors in high-income countries (Hille and Möbius, 2019). This, however, requires a renewable energy technology producing sector, which most developing countries lack. Hence, ambitious carbon pricing with prices currently seen in rich countries will likely be implemented at higher levels of economic development.

Carbon pricing also increases the price of energy use for households with negative consequences for household welfare. In rich countries, poorer households spend on average a higher share of their income on energy such as electricity, transport fuels or natural gas. In poorer countries, the effects of rising energy prices are typically progressive, as richer households tend to own more energy-processing durables such as household appliances, cars or motorbikes, although effects tend to be country- and fuel-specific (Dorband et al., 2019; Arze del Granado et al., 2012; Sterner, 2011). Poor households that own such assets experience large welfare losses due to higher energy expenditure shares (Renner et al., 2018a,b). Hence, even if average welfare losses of poor households tend to be smaller in developing countries, these losses in disposable income need to be compensated in order to avoid increases in poverty or a slow-down of poverty reduction trends.

In theory, tax revenues from carbon taxes can be used for compensation schemes that prevent welfare losses of the poorest population (Budolfson et al., 2021). However, revenue recycling schemes require an infrastructure that can adequately target the most affected population. Many developing countries do not have universal income tax systems, and second-best compensation schemes reliant on, for instance, survey data, can only imperfectly identify households in need of assistance (Hanna and Olken, 2018). Identification of appropriate compensation schemes remains one of the biggest challenges for equitable burden sharing and the resulting political acceptance of environmental taxes in developing countries. Moreover, rent-seeking behaviour of political elites may prevent distributional policies tailored towards the poorer population. Hence, implementation of effective compensation schemes in the near future may only be feasible for countries exhibiting good governance and comparatively high state capacity. In addition, higher prices for fossil cooking fuels such as LPG may lead to a slow-down of clean-cooking fuel adoption, or even dis-adoption of such fuels.

1.4 Contribution to the literature

In this dissertation, I examine the impacts of rising energy prices in countries from three world regions that include both lower-middle income countries, including Ghana and Indonesia, and an upper-middle income country, that is, Mexico. Each of the four following Chapters looks at a different dimension of the impact of rising energy prices on either households or firms. All Chapters employ a partial equilibrium approach with an emphasis on heterogeneous impacts using microdata. The drawback of examining partial equilibrium effects are lack of indirect effects and hence only limited mid- to long-term validity of results. However, they provide valuable information on initial reactions to price increases that can inform policy decisions as well as economic theory and modelling of mid- to long-term effects. Thus, these studies are complements to computable general equilibrium models (e.g. Carbone and Rivers, 2017; Fullerton and Heutel, 2007) or integrated assessment models that also include impacts on the natural world (Nordhaus, 2019; Weyant, 2017). Partial equilibrium studies can potentially inform such models by, for instance, assessing whether or not generator use matters for reactions of firms to price increases. Moreover, short-term effects are likely more important than long-term consequences for opposition against climate policy, and hence provide valuable information for policy design. Identifying heterogeneous effects allows for adequate design of, for instance, compensation schemes or other measures aimed at mitigating adverse consequences of mitigation policies.

Chapter 2 looks at the impact of rising energy prices on an important segment of the economy in developing countries: Many low- and middle-income countries are characterized by an abundance of micro- and small-sized enterprises (MSEs), which often dominate the employment share of the whole economy (Li and Rama, 2015). In Mexico, they provide roughly 47 percent of total employment. The sector is typically characterized by small, low-productivity firms (*survivalists*), with some high-productivity firms (*top-performers*) and some firms with the potential for high productivity (*gazelles*). Early development theories have argued that the emergence of large firms in modern sectors would absorb many employed in the informal sector (Grimm et al., 2012). This has, to a large extent, not materialized to date, and some even expect that the informal sector will be the dominant driver of job creation in developing countries for years to come (Rodrik, 2021). Lack of high-quality data on MSEs in developing countries have so far prohibited analyses of the impact of energy prices. This Chapter provides a first assessment of the impact of energy price increases on MSEs using a representative dataset. Hence, the findings have validity for the whole universe of MSEs in Mexico, instead of only for a small, accessible part of small businesses in e.g. larger urban cities.

My co-authors and I calculate first-order profit losses of the direct effect of energy price increases. These first-order effects will quickly be followed by adjustments of the firms. Nevertheless, identification of immediate effects is important from a political economy perspective, because they play a role in how losses due to price reforms are perceived in this important segment of the Mexican economy. We find that many MSEs, especially those with comparatively small profit margins, do not use energy inputs in their businesses. Those fuel or electricity using firms at the bottom of the profit distribution are affected substantially by energy price increases, because high energy cost shares meet low profit margins resulting in large profit losses. Further, fuel price increases lead to higher profit losses compared to electricity price increases. Substitution elasticities, estimated under strong assumptions, indicate that larger MSEs slightly reduce energy consumption, which mitigates profit losses in the mid-term. The self-employed reduce fuel consumption drastically and increase own-labour supply, while we find no behavioural differences between formal and informal firms. Reduced-form regressions further indicate that many firms in the food processing sector increase output prices in response to fuel price increases. We propose to (temporarily) increase transfers to poor households, and linking them to energy price policy. This would not only mitigate real economic consequences, but would also potentially increase political support for energy price measures such as fossil fuel subsidy removal or carbon pricing. Further, household support measures are likely to be more feasible to implement than measures aimed at the informal sector due to targeting issues.

In Chapter 3, I turn the focus on the issue of generator use in developing countries. Since electricity supply is often both insufficient and unreliable in these countries, many firms invest in generators in order to avoid prolonged production process interruptions and be able to power large machinery and thus expand production (Alby et al., 2012). A growing literature has found that firms that invested in generator capacity exhibit higher performance compared to other firms in countries with frequent power outages (Abeberese et al., 2019; Falentina and Resosudarmo, 2019; Cole et al., 2018; Allcott et al., 2016). Only few papers investigate the impact of rising energy prices on firms in developing countries (e.g. Abeberese, 2017; Rentschler and Kornejew, 2017). So far, no paper has investigated the impact of fuel price increases on firms with a focus on generators. Such increases will likely affect generators-using firms differently compared to other firms. Hence, Chapter 3 looks the impact of diesel fuel price increases on performance measures of large Indonesian manufacturing firms. Due to data limitations, we cannot investigate the average treatment effect of rising energy prices. Instead, this Chapter looks at the differential impact on performance measures of generator-using firms versus those that do not use generators. Changes in relative prices of fuels will also influence the attractiveness of continuing to use generators. This will have implications for the environmental performance of manufacturing firms, since diesel generators operate at much lower efficiency levels than power plants.

We indeed find differential impacts between firms with and without prior generator use. Diesel price increases have negative effects on firms that use generators compared to non-using firms: Total sales, value added, and material input use decline, while reductions in labour demand prevent productivity losses. At the same time, fuel price increases disincentivize generator use, as the share of firms using any generator dropped sharply after strong diesel price increases in 2005. While we find no direct effect of fuel price increases on energy and emission intensity, dis-adoption of generators is associated with a 20 percent decrease in emission intensity at the firm-level, on average. With rising electricity prices, generator use becomes more attractive, and many firms adopted generators after stark electricity price increases in 2010. However, the intensity of generator use – that is, the share of self-generated electricity – declined in these years, most likely due to a combination of high diesel fuel prices and improvements in the reliability of electricity supply. These findings have implications for energy price policy in countries with poor grid electricity quality and a high prevalence of generator-using firms. Investment in the electricity grid will pay a double dividend: It will improve the environmental performance of (manufacturing) firms without compromising (and likely improving) their economic performance. Further, the findings indicate that increasing electricity tariffs without investment into the expansion and reliability of the electricity grid will lead to higher total territorial GHG emissions by incentivizing generator adoption of large manufacturing firms. Investment in the electricity grid should be prioritized before implementing ambitious carbon pricing to prevent competitiveness losses in the manufacturing sector.

The last two Chapters shift the focus to households in lower-middle- and upper-middle-income countries. Chapter 4 looks at the distributional implications of carbon taxation in Mexico. Substitution elasticities – estimated by means of a censored quadratic almost ideal demand system that accounts for selection bias – form the basis of second-order welfare effect estimates that take into account behavioural reactions of households to price increases. Moreover, these substitution elasticities allow the assessment of the short-run, consumption-based CO_2 reduction potential of carbon pricing. We find that first- and second-order approximations of welfare effects are quite similar in Mexico. Welfare effects of electricity and gas price increases are regressive, while taxation of motor fuels is progressive. Further, short-run emission reductions due to household consumption adjustments can be substantial. However, these effects crucially depend on how revenue is recycled. Our analysis shows that emission abatement effectiveness combined with moderate and manageable adverse distributional impacts renders the carbon tax a preferred mitigation instrument. However, the inclusion of CH_4 and N_2O in a carbon tax regime is not advisable, as we find a large effects on food prices with adverse consequences for the poverty incidence and only limited additional emission saving potential.

Finally, in Chapter 5, we investigate the impact of a fossil fuel subsidy removal on cooking fuel choice in Ghana. This is, to our knowledge, the first study that provides quasi-experimental evidence of fossil fuel subsidy reform on household behaviour in a developing country. In SSA, households account for about two-thirds of total energy consumption (IEA, 2019), and cooking makes up the lion's share of that energy demand. Most households, including in Ghana, mostly use firewood in rural and charcoal in urban areas, but more and more households have adopted LPG – a cleaner fuel associated with less indoor air pollution – as main cooking fuel. Fossil fuel subsidy removal may lead households to switch back towards using transition and traditional fuels for cooking, with adverse consequences for human health and forest degradation (WHO, 2016; Bailis et al., 2015).

Ghana introduced a subsidy reform in 2013, which increased LPG prices by about 50 percent and transport fuel prices by about 20 percent. We thoroughly investigate the impact of the subsidy removal on main cooking fuel choice, charcoal consumption quantities and LPG expenditure by means of an unconventional difference-in-difference research design. We use a different survey that took place during 2005-2006 to compare fuel use trajectories between households that were surveyed during 2013, and households that were surveyed during 2006. This allows us to mitigate identification concerns related to seasonal fuel use patterns, which are known to exist due to solid biomass supply changes during the rainy seasons. We find that households "stepped down the energy ladder": The share of households who mainly use firewood for cooking increased by about 3 percentage points in urban areas. In rural areas, the impact is larger at about 5 percentage points, but unreliably estimated. Further, average charcoal consumption in urban areas increased by about 18 percent. Lastly, impact estimates suggest that LPG expenditure remains constant for a 50 percent price increase, indicating that quantity consumed dropped. Back-on-the-envelope cost-benefit calculations suggest that the subsidy removal increased cooking-related GHG emissions due to higher charcoal demand in urban areas, and that the social costs are likely a little higher than fiscal savings of the reform. Our findings highlight the ambiguous impacts of removing LPG subsidies in developing country contexts where they contribute to the adoption and use of clean cooking fuels.

Chapter 2

How vulnerable are small firms to energy price increases? Evidence from Mexico

2.1 Introduction

The responses of micro- and small-sized enterprises (MSEs) to economic policies and shocks are important. Effects on firm profits and performance directly affect the livelihoods of many in developing economies, where these firms provide employment to many (Kanbur, 2017; Li and Rama, 2015). Energy price reforms have repeatedly sparked social unrest in a number of developing (and some developed) economies. While the direct negative impact on consumer welfare arguably plays an important role for opposition to subsidy reforms (Labeaga et al., 2020; Coady et al., 2018; Renner et al., 2018b), the adverse impact on MSEs could be substantial. This is why these often informal MSEs, with their entrepreneurs and (family) workers, may comprise another important opposition group to policies that increase energy prices, that is, subsidy reforms or carbon pricing, in developing countries. Indeed, among those protesting against fuel price increases – whether in Ecuador, Kenya, Mexico, or even China (Cabrera, 2019; Nyambura and Ombok, 2018; Buscaglia, 2017; China Labour Bulletin, 2017) – were truck and taxi drivers, who are often self-employed. In addition, workers engaged in other small-scale activities, such as street kitchens, may also be vulnerable to such increases.

The Mexican government phased out energy subsidies between 2012 and 2018. During this period, gasoline and liquefied petroleum gas (LPG) prices in Mexico City increased by 95 percent and 79 percent respectively.[1] The so-called *gasolinazo*, a price spike of almost 20 percent within a single week in January 2017, led to riots, looting, and the arrest of hundreds of

This is joint work with Ana Karen Negrete and Jann Lay.

[1]Figure A2.1 in Appendix A shows price development in Mexico City over time.

demonstrators in Mexico (Buscaglia, 2017). The national alliance of microenterprises (Anpec) reported that many MSEs struggled to remain in business and that they increased product prices by 5–15 percent (Gonzalez, 2017). Beyond such anecdotes, there is limited evidence on the impacts of fuel and energy price changes on firms in developing countries. This is the case despite the potential relevance of the welfare impacts on firm owners, the self-employed, and workers, as well as the related importance for the political economy of the energy sector and price reform – particularly fossil fuel subsidy reform and carbon pricing.

Only few studies have assessed the impact of energy price changes on firms in developing countries.[2] For example, Sadath and Acharya (2015) find that the fluctuation of energy prices adversely affects investment in the Indian manufacturing industry. Abeberese (2017) shows that rising electricity prices affect industry choice and slow down the productivity growth of Indian manufacturing firms. Rentschler and Kornejew (2017) exploit regional price variation from cross-sectional data to reveal that small manufacturing firms in Indonesia rely on a number of strategies to cope with higher energy prices, namely absorption, pass-on through higher output prices, input substitution, and increasing resource efficiency.

In this paper, we use a rich representative dataset from 2012 for formal and informal MSEs in Mexico to address the important evidence gap on the impact of fuel price increases on developing country firms. To illustrate the potential effects on MSEs, we calculate first-order (FO) profit losses from energy price increases, interpreted as upper bound estimates of the direct and immediate effect.[3] Further, using a pooled cross-section with data from 2010 and 2012, we estimate input-demand substitution elasticities for labor, electricity, and fuels that form the basis of an estimate of second-order (SO) effects, admittedly under fairly restrictive assumptions. Lastly, reduced-form regressions of unit output prices on fuel prices provide evidence of the ability of MSEs to pass on input price increases to consumers.

These analyses do not allow for clean causal attribution from price changes to profit and behavioral changes. Instead they provide what we think are empirically relevant indications of the potential vulnerability of small firms to fuel price increases in a developing country. Further, the analysis delivers important descriptive insights into the incidence of such price reforms, and is indicative of the capacity of even small firms to adjust. This is – to our knowledge – the first paper that provides such assessment with representative data from small and informal firms across all sectors.

The remainder of this paper is organized as follows. Section 2.2 describes the dataset and provides descriptive statistics on Mexican MSEs and their energy use patterns. Section 2.3

[2] Relatively more attention has been paid to the effects of electricity shortages and blackouts on firms in developing countries (see e.g. Falentina and Resosudarmo, 2019).

[3] Data constraints inhibit an analysis of firm reactions during the *gasolinazo*. Our estimated impacts do not capture the impact of other types of shocks that may accompany a price shock, for example closures of gas stations (that is, fuel shortages).

presents the methodology for computing first- and second-order effects on profits. Section 2.4 presents the results, while Section 2.5 concludes.

2.2 Data and descriptive statistics

We link the National Survey of Microenterprises (ENAMIN) and the National Employment Survey (ENOE), a labor force survey (INEGI, 2012), both collected by the National Institute of Statistics and Geography. Included are MSEs with up to 10 workers in commerce, services, transport, and construction, and up to 15 workers in manufacturing. The resulting dataset has comprehensive information about every entrepreneur and the corresponding economic unit.[4] By design, ENAMIN is representative for both formal and informal MSEs, including those that lack premises. Approximately 78 percent of all MSEs surveyed in 2012 were informal – which is defined as not paying taxes. Sixty percent of the firms operate in urban areas.

We use the latest round of the survey, ENAMIN 2012, to simulate both first- and second-order profit losses caused by energy price increases. To estimate own- and cross-price elasticities underlying the SO profit losses, we use a pooled cross-section of the two latest rounds of the survey, ENAMIN 2010 and ENAMIN 2012, to capitalize on temporal variation in fuel prices. For the analysis of output price adjustments, we can add ENAMIN 2008, which is not suitable for the elasticity estimation due to data gaps. The descriptive statistics here are based on the ENAMIN survey of 2012.

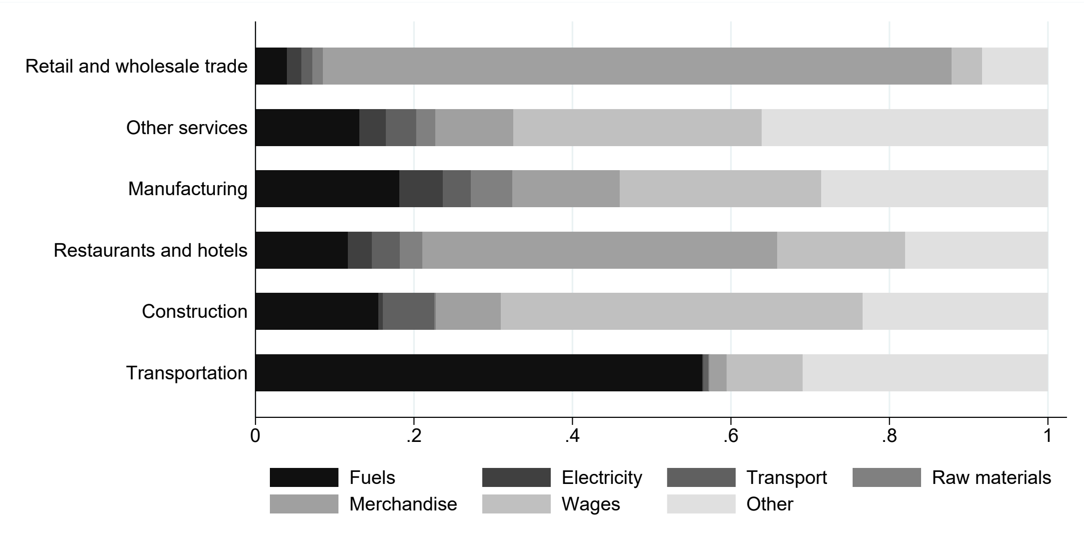


Figure 2.1: Input cost structure in 2012, by industry

The 2012 sample comprises 23,659 observations (excluding those with missing profit values), representing about 7.1 million MSEs in Mexico. Figure 2.1 shows the average cost struc-

[4]For details on the construction of price data, see Appendix B.

tures of these firms by industry after applying sample weights. The relative importance of electricity and fuels inputs measured by their cost share varies considerably across industries. We group these enterprises into six industries, with retail and wholesale trade dominating the universe of MSEs, but with clearly less than half of the production units (39 percent).

Firms engaged in the transport sector spend nearly 60 percent of their total cost on fuels and little on electricity. Typically, in a range between 15 and 20 percent of total cost, combined fuel and electricity expenditure share is relatively high across all industries – except in retail and wholesale trade, where it is about 5 percent. Fuel costs are clearly more important than electricity costs: For all firms, fuel costs account for 18 percent of total cost on average, while electricity accounts for 6 percent thereof (see Table 1 below). This implies an average monthly expenditure of USD 63 on fuels and USD 15 on electricity. The firms with the greatest electricity expenditure share can be found in the manufacturing sector.

Table 2.1 presents key summary statistics regarding MSEs (columns 1-3). On average, businesses generate monthly profits of approximately USD 321.[5] The median firm size is 1, hence most are one-person firms. Slightly more than half of firms are owned by females, and most firms (about 80 percent) are informal. It is slightly more common that MSEs have nonzero expenditure on electricity (47 percent) than on fuels (45 percent), despite the higher share of the latter in total costs. This means that, for users of the respective energy type, expenditure shares are much higher than the reported averages of 6 percent (electricity) and 18 percent (fuel). For those that actually use fuels for production, the average expenditure share is 38 percent (12 percent for electricity) of total costs.

Table 2.1 also shows descriptive statistics by profit quartiles (columns 4-7). The higher the profits, the more common it is for them to have non-zero expenditures on electricity and fuels. The take-up rate is higher for the case of fuels. Also, there is a positive correlation between profits and the consumption of electricity (kWh). Correspondingly, the greater monthly profits are, the higher monthly expenditure on electricity will be in absolute terms. In relative terms, however, firms with high profits pay less for electricity relative to total costs. Hence, firms with small profit margins that use energy are likely to experience the largest shock when energy prices rise.

One feature of small firms in developing countries – including in Mexico – is that they often operate informally: that is, they do not follow government regulation (e.g. tax payments or enrollment of workers in social security schemes).[6] In contrast to the formal sector, the informal

[5]We use monthly profits, as captured by the question: "How much do you normally earn after deducting expenses?" This is because the measurement error is smaller than the computation of income minus costs (Mel et al., 2009).

[6]A further distinction can be made between "informality" and "illegality" (Busso et al., 2012). Firms may not need to adhere to a particular regulation, and hence are informal but legal, whereas other firms may evade regulation, therefore operating both informally and illegally. Constituting a third type of informality are those firms that avoid regulation: for example, choosing to remain small to avoid a certain regulation from applying to

Table 2.1: Firm characteristics and energy expenditure in 2012

				Profit Quartiles (mean)				Formality (mean)	
	Mean	Median	SD	1st	2nd	3rd	4th	Formal	Informal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
General Characteristics									
Monthly profits	321	197	557	44	147	312	906	585	251
Labor (weekly hours)	63	48	62	34	54	69	103	103	52
Firm size (total staff)	1.59	1.00	1.09	1.21	1.43	1.61	2.26	2.24	1.42
Female owner	0.51	1.00	0.50	0.80	0.59	0.35	0.23	0.40	0.54
Informal firm	0.79	1.00	0.41	0.93	0.84	0.76	0.57		
Electricity									
Share of users	0.47	0.00	0.50	0.33	0.46	0.50	0.61	0.83	0.37
Exp. share (full sample)	0.06	0.00	0.13	0.07	0.06	0.05	0.05	0.06	0.06
Exp. (users)	0.12	0.06	0.16	0.19	0.13	0.10	0.07	0.08	0.14
Avg. exp. (USD)	15	0	69	4	10	16	35	46	7
kWh (estimate)	101	0	211	41	84	109	186	244	62
Fuels									
Share of users	0.45	0.00	0.50	0.20	0.37	0.55	0.72	0.60	0.40
Exp. (full sample)	0.18	0.00	0.29	0.11	0.15	0.23	0.25	0.15	0.19
Exp. share (users)	0.38	0.29	0.31	0.45	0.38	0.40	0.34	0.25	0.43
Avg. exp. (USD)	63	0	181	9	28	70	165	118	48
Sectors									
Retail and wholesale trade	0.39			0.49	0.44	0.32	0.29	0.45	0.37
Services	0.23			0.17	0.20	0.24	0.30	0.29	0.21
Manufacturing	0.15			0.21	0.14	0.13	0.13	0.10	0.17
Restaurants and hotels	0.13			0.10	0.15	0.14	0.10	0.10	0.13
Construction	0.07			0.01	0.04	0.11	0.12	0.02	0.08
Transportation	0.04			0.01	0.02	0.05	0.06	0.04	0.03
N	23659			6008	6640	6087	4924	4988	18671
N with sample weights (millions)	7.1			1.9	2.0	1.8	1.4	1.3	5.8

Notes: Exp. = expenditure. As explained in Appendix B, electricity consumption in kWh was estimated by taking block tariffs into consideration. Nominal values correspond to 2016 MXP and are reported in USD. The considered MXP-USD exchange rate is 18.102 which, just as with the GDP deflator (INPC), corresponds to February 2016.

one is typically characterized by an abundance of small firms operating at low levels of productivity (*survivalists*), although some firms stand out in terms of productivity (*top performers*) or potential for productivity (*constrained gazelles*) (Grimm et al., 2012). In columns 8 and 9 of Table 2.1, we present descriptive statistics for formal and informal firms respectively. Average profits of formal firms are more than twice as large, and these firms are also larger (2.24 workers versus informal firms 1.42 on average). Further, energy use is more common among formal

them (Kanbur, 2017).

firms, with 83 (60) percent using any electricity (fuel) compared to 37 (40) percent among informal firms. However, those of the latter that use electricity or fuels have higher energy cost shares than formal firms that do so. Electricity makes up 14 percent of total costs for electricity-using informal firms on average, compared to 8 percent for formal firms. Fuel cost shares are even higher: fuels make up 43 percent of total costs for informal firms, compared to 25 percent of formal firms on average (only fuel-using firms).

2.3 Methodology

In theory, firms have several options to avoid profit losses when energy prices rise (Rentschler et al., 2017): (i) They can substitute toward other factor inputs; (ii) pass on the price shock; and, (iii) increase both material and energy efficiency. We analyze the first and second types of reaction, which we believe are indicative of the vulnerability to price shocks in the short term. Large efficiency increases are unlikely in the short run in response to energy price changes among the smallest firms due to capital constraints inhibiting quick investments (Hernandez-Trillo et al., 2005), although implementing measures that require minimal investment may still be feasible. Firms may also switch their contracted electricity tariffs in response to related increases, but although this comes at little cost to the firm the impacts of such adjustment are expected to be only minor.

We examine both the first- and second-order impacts of price changes, with the latter allowing firms to change the input composition. Both these analyses look at direct effects only: that is, we only examine fuel and electricity price changes and ignore the potential subsequent ones in transport costs and intermediate inputs that will, again, also affect firm profits. FO impacts will be largest for those firms with small profit margins and significant energy cost shares. For SO effects, we expect some behavioral differences with regard to formal and informal firms (see Section 2.3.2).

2.3.1 First-order profit losses

As a first approximation to the effects of energy price changes, we compute the FO impacts: that is, the impacts under the assumption that firms do not change the input composition or the output quantity, and that they cannot pass the burden on to their customers in the form of increased prices regarding products or services. This simplification ignores firms' adjustments of production after price increases, so the FO effects should be thought of as an upper-bound estimate to the direct short-term profit loss. We obtain the FO estimate via subtracting decreased profits from initial profits, and then express it as the percentage share of additional costs in initial profits:

$$FO_{fj} = \frac{\Pi_f - (\Pi_f - \Delta C_{fj})}{\Pi_f} \times 100 = \frac{\Delta C_{fj}}{\Pi_f} \times 100 \tag{2.1}$$

with

$$\Pi_f = y_f - C_f = q_f \times p^{\text{output}} - C_f \tag{2.2}$$

and

$$\Delta C_{fj} = C_{fj,1} - C_{fj,0} = (1 + \Delta p_j) \times C_{fj,0} - C_{fj,0} = \Delta P_j \times C_{fj,0} \tag{2.3}$$

where Π are profits, defined as output quantity times output price p^{output}, and ΔC is the cost increase: that is, the difference in costs in $t = 1$ and $t = 0$ caused by price change ΔP_j (expressed as a ratio of initial price, i.e. $\Delta P_j = p_{j,t=1}/p_{j,t=0}$). Subscript j denotes either fuels or electricity, and f indicates the firm. Thus, ceteris paribus, profits of firm f decrease by FO percent when the price of energy input j increases by ΔP_j.

2.3.2 Input-demand elasticities

Substitution effects can provide valuable information about the SO effects of energy policies on economic agents (Berndt and Wood, 1975). As the MSE sector is a key employer in Mexico and many other developing economies, we are particularly interested in the effect of rising energy prices on labor demand. In theory, labor and fuels can be substitutes or complements, depending on the production technology. The substitution possibilities between electricity and fuel are also relevant for labor demand: when a fuel price increase is mainly adjusted for by increasing electricity demand, labor demand might not be significantly affected. If electricity and fuel are complements and energy not easily substituted by labor, labor demand would fall with higher fuel (or electricity) prices. Two recent studies of substitution possibilities between labor and energy for European firms found that these two inputs are indeed substitutes (Bardazzi et al., 2015; Haller and Hyland, 2014). Furthermore, labor seems to be more easily substitutable by energy inputs than the other way around.

We suggest three rationales for the substitutability of labor and energy that seem particularly relevant in our context. First, firms might change from using motorized forms of transportation (for example, via motorbike) to using public or manual transportation (by foot or bicycle). This may be particularly important for informal firms. Second, firms within industries might change technology and/or specific activity toward less energy-intensive production. In particular informal firms with very low fixed capital may be able adjust technologies quickly and exhibit high labor demand elasticities with respect to energy. Yet, if firms adjust by investment in more energy-efficient technologies, we may observe more rapid and bigger adjustments in larger (formal) firms with better access to capital. Third, the entry and exit of firms are also implicitly reflected in the estimated elasticities, because we pool ENAMIN 2010 and ENAMIN 2012. Hence, we observe different firms in these two years. As such, what looks like flexibility of existing firms may actually be driven by high rates of entry and exit within specific sectors, and we may overestimate actual behavioral reactions with respect to cross-price elasticities. This churn may be more prevalent among informal MSEs.

To derive input-demand elasticities, we estimate a translog cost-function for three inputs, namely fuels, electricity, and labor using external, regionally disaggregated price data (see Appendix B for details on price data and Appendix C for the technical details of the cost-function and elasticity estimation). It is common to estimate a full input-demand system that also includes capital and materials (Bardazzi et al., 2015; Haller and Hyland, 2014), although there are examples that exclude some of these inputs (Woodland, 1993). Due to a lack of high-quality data on intermediate inputs and capital prices, we opt to exclude these inputs and instead rely on the assumption of separability between capital and material inputs on the one hand and fuels, electricity, and labor on the other. Further, not all MSEs employ all of the three inputs of our model specification. To avoid problems arising from the censored nature of the data, we follow Woodland (1993) and estimate the model for two subsamples of firms – each with positive expenditure for all three inputs.[7] The first sample includes firms employing hired labor. The second sample consists of one-person MSEs, that is, the self-employed. For these firms, we estimate substitution elasticities for own labor instead of hired labor under the assumption that the prevailing median regional wage rate is the shadow price. This elasticity determines the extent to which the self-employed increase their own-labor supply as a response to rising energy prices.

For the estimation, we pool the ENAMIN survey waves of 2010 and 2012 and merge these with regional price data (except for electricity prices of formal firms, where we only have national prices; see Appendix B for details). As fuel and electricity prices were heavily regulated by the Mexican government (IEA, 2016b) and MSEs can be assumed to be price-takers, the variation is arguably exogenous. In most cases, the identifying variation is a price increase. Only in a very few cases does the regional average of the residential electricity price decline between 2010 and 2012. We are able to obtain more variation in electricity prices by matching estimated consumption levels with the price schedule of the residential block tariff. This procedure is not without problems: Firms choose their level of electricity consumption and thus self-select the consumption block. If they take the block-tariff structure into account this specification potentially suffers from endogeneity, as the amount of electricity consumed determines the price and vice versa. There are some hints in the literature (Ito, 2014) that electricity users react to average rather than marginal prices in nonlinear price schedules, which suggests that the endogeneity bias may be attenuated. However, the bias may still be large regardless.[8]

[7] Overall, 23.6 percent of the MSEs in our sample use both energy inputs in 2012. The estimated elasticities are thus specific to a subsample with firms that tend to be larger and have higher profits.

[8] Attempts to consider the block-price structure in the context of cost-function estimation are nonexistent, to our knowledge, although some authors do model consumer demand under multipart pricing (Reiss and White, 2005).

There are a few additional points that one needs to be aware of when interpreting the estimated elasticities, and hence SO effects. First, as mentioned above, we assume separability between electricity, fuels, and labor on the one hand and all other inputs – including capital – on the other. Since we thus assume that investment decisions cannot be affected by price increases, the elasticities are to be interpreted as short-term. Second, we control for a number of firm characteristics and include several sets of fixed effects.[9] Our controls include dummies that capture the block structure of electricity prices and we thus compare firms that have a similar (but not identical) level of electricity consumption. Third, we implicitly assume that MSEs do not exit the market due to higher energy prices (albeit this may not fully hold) and that microenterprises continue to use specific inputs (such as paid labor). Hence, the labor demand decision is only evaluated at the intensive margin, and elasticity estimates will reflect entry and exit of firms to an unknown extent.

2.3.3 Second-order profit losses

We compute SO profit losses using estimated substitution elasticities. The change in costs (when the price of input j increases) consists of three parts: changes in fuel, electricity, and labor input costs.

$$
\begin{aligned}
\Delta C_f &= \Delta C_{fg} + \Delta C_{fe} + \Delta C_{fl} \\
&= (E_{fg,1} - E_{fg,0}) + (E_{fe,1} - E_{fe,0}) + (E_{fl,1} - E_{fl,0}) \\
&= (p_{g,1}x_{fg,1} - p_{g,0}x_{fg,0}) + (p_{e,1}x_{fe,1} - p_{e,0}x_{fe,0}) + (p_{l,1}x_{fl,1} - p_{l,0}x_{fl,0})
\end{aligned}
\tag{2.4}
$$

Subscripts g, e, and l denote fuels, electricity, and labor respectively. E denotes the value of expenditures, x is the input quantity consumed, and 0 and 1 indicate the periods before and after the price change. The quantity of input k after a price change for input j in period 1 is given by

$$
x_{kj,1} = \left(1 + \frac{\eta_{kj}}{100}\right) \times \frac{E_{k,0}}{p_{k,0}} \tag{2.5}
$$

where η denotes the elasticity between two inputs. The SO estimate represents the percentage reduction of profits of firm f when the respective energy price of energy input j increases by $(\Delta p \times 100)$ percent. The elasticities used for the computation are industry-specific, except for the construction and transportation ones. Here, sample sizes are too small, so we use elasticities from the full sample estimation. For one-person firms, we provide two types of SO effects: one without labor input and one with imputed costs of additionally employed own labor.

[9]We include age of entrepreneur, age of entrepreneur squared, sex-dummy of entrepreneur, age of the firm, years of education of the owner, whether or not it is a one-person firm, capital stock, a year dummy, regional dummies, industry dummies, and electricity block-tariff dummies as additional explanatory variables. All continuous variables are logarithmic.

2.3.4 Output price adjustment

The above first- and second-order effects are computed under the assumption that output prices remain constant. However, some firms will also be able to pass on the increased input costs to consumers by raising prices. The capacity to do this will differ between industries and products, and will generally be lower for tradables than for nontradables. Further, formal and informal firms may differ in their ability to increase output prices: informal firms are likely to operate in very atomistic markets with little price-setting power, but they also have very low margins and may operate close to a subsistence floor. In other words, they may not have other options than raising prices or exiting.

We estimate – in reduced form – the reaction of output prices to fuel price changes (plus firm characteristics X_{frt}, regional η_r, and time fixed effects τ_t). That is, we estimate the following regression equation:

$$ln(p_{frt}^{\text{output}}) = \beta_0 + \beta_1 ln(p_{rt}^{\text{fuels}}) + \beta_2 X_{frt} + \eta_r + \tau_t + \theta_{pu} + \mu_{frt} \tag{2.6}$$

We will only be able to estimate this equation for a small subset of firms that produce relatively homogenous products without major quality differences. We refrain from converting units of quantity, and instead include product-unit fixed effects θ_{pu}. In contrast to the above analyses, this reduced-form estimate implicitly takes into account the price changes in intermediates and transport costs induced by the fuel/electricity price change.

2.4 Results

2.4.1 First-order profit losses

We first divide average estimates into a full sample and sub-samples containing MSEs with strictly positive electricity or fuel demand ("users only"). We then provide impact measures over profit percentiles. Table 2.2 depicts averages of FO estimates for a 1 percent price increase by sector. On average, the FO estimate is 0.2 percent for fuels and 0.07 percent for electricity. Hence the *gasolinazo* price increase of about 20 percent within a single week would have translated into a 4 percent profit reduction, a sizable effect. This indicates MSEs' considerable vulnerability to fuel price increases – less so to electricity prices. In addition, MSEs exhibit considerable heterogeneity. For both fuel and electricity price increases, the standard deviation of the FO estimate is three times its mean for the full sample, and two times its mean for users.

We also find substantial heterogeneity among MSEs by sector. The highest FO effects – at 1.27 percent – are in the transport industry, in which profit reduction is even higher than price increases. The restaurants and hotels industry is also relatively vulnerable to fuel price increases, with a 0.23 percent profit reduction. For electricity, the highest short-term effects

Table 2.2: FO estimates by sectors

Sector		Fuels: Full sample	Fuels: Users only	Electricity: Full sample	Electricity: Users only
Retail and wholesale trade	Mean	0.14	0.46	0.10	0.21
	SD	(0.45)	(0.72)	(0.30)	(0.42)
	N	9214	2820	9201	4133
Services	Mean	0.14	0.33	0.05	0.09
	SD	(0.38)	(0.53)	(0.13)	(0.15)
	N	5347	2274	5326	3161
Manufacturing	Mean	0.22	0.46	0.06	0.12
	SD	(0.63)	(0.86)	(0.18)	(0.23)
	N	3652	1746	3637	2018
Restaurants and hotels	Mean	0.23	0.30	0.05	0.10
	SD	(0.44)	(0.48)	(0.14)	(0.18)
	N	2978	2268	2978	1534
Construction	Mean	0.14	0.34	0.00	0.05
	SD	(0.32)	(0.43)	(0.02)	(0.08)
	N	1602	681	1602	88
Transportation	Mean	1.27	1.42	0.01	0.21
	SD	(2.29)	(2.38)	(0.11)	(0.61)
	N	832	743	833	27
Formal	Mean	0.25	0.42	0.15	0.17
	SD	(0.76)	(0.94)	(0.33)	(0.35)
	N	4979	3003	4967	4130
Informal	Mean	0.19	0.47	0.04	0.12
	SD	(0.63)	(0.92)	(0.17)	(0.27)
	N	18646	7529	18610	6831
Total	Mean	0.20	0.46	0.07	0.14
	SD	(0.66)	(0.93)	(0.22)	(0.30)
	N	23625	10532	23577	10961

of price increases on profits are found in the retail and wholesale trade industry (0.1 percent). When looking at fuel users in this industry, the effect is also large with 0.46 percent. This pronounced difference between the full and the users-only sample estimates is because only around 45 percent of firms in the retail and wholesale sector use fuel.

Average FO estimates for formal firms are generally larger than for informal ones. The higher share of energy costs of formal firms, which, ceteris paribus, leads to higher profit losses, thus outweighs the effect of larger profit margins that mitigates the adverse impacts on costs. The only exception are FO estimates for fuel users, which stand at 0.47 among informal firms compared to 0.42 percent for formal firms. For electricity, the average FO estimate is much higher for formal firms at 0.15, compared to 0.04 for informal ones, while the difference between estimates for users is less pronounced (0.17 compared to 0.12 respectively). Hence, the electricity FO estimate for the full sample of informal firms exhibits considerable dispersion, with a standard deviation that is more than four times larger than the estimate. This reflects the relatively large impacts on fuel-using informal firms combined with the relatively high share of informal firms that do not use any fuel (details below).

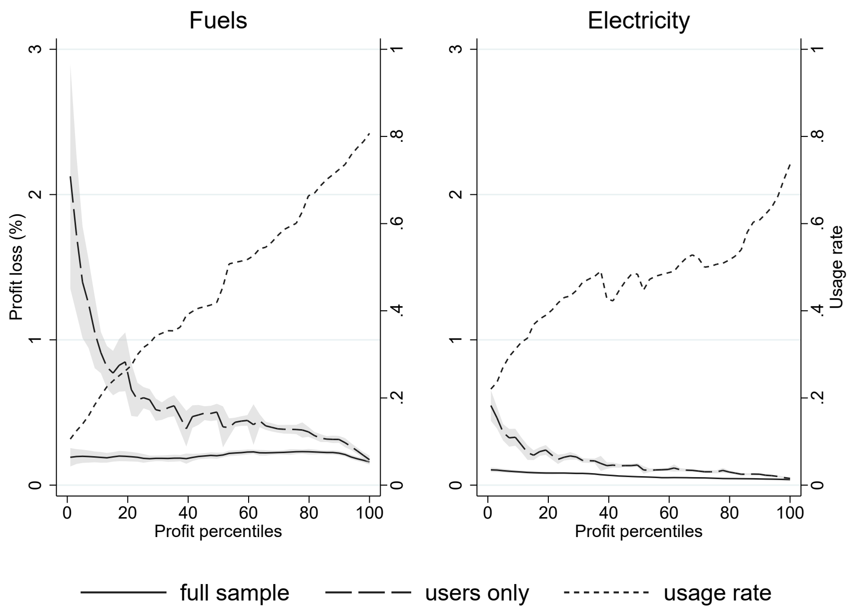


Figure 2.2: FO estimates across profit percentiles

Figure 2.2 shows the incidence of estimated FO effects as well as the average energy usage rate across profit percentiles for the full sample.[10] The profit losses are hefty for fuel or electricity users at the bottom of the profit distribution, with FO estimates for fuel reaching 2 percent. Even for electricity users (about 20 percent among low-profit firms), a 1 percent electricity price increase translates into a 0.5 percent profit loss. For these firms, low profits meet a high share of fuel or electricity costs. While the effects are thus highly regressive among users, the average FO estimates – including nonusers – are stable across the profit distribution (or slightly

[10]The figure shows nonparametric distributional curves with a 95 percent confidence interval, calculated with a kernel-weighted local polynomial regression using the Epanechnikov kernel function.

progressive for fuels and slightly regressive for electricity).

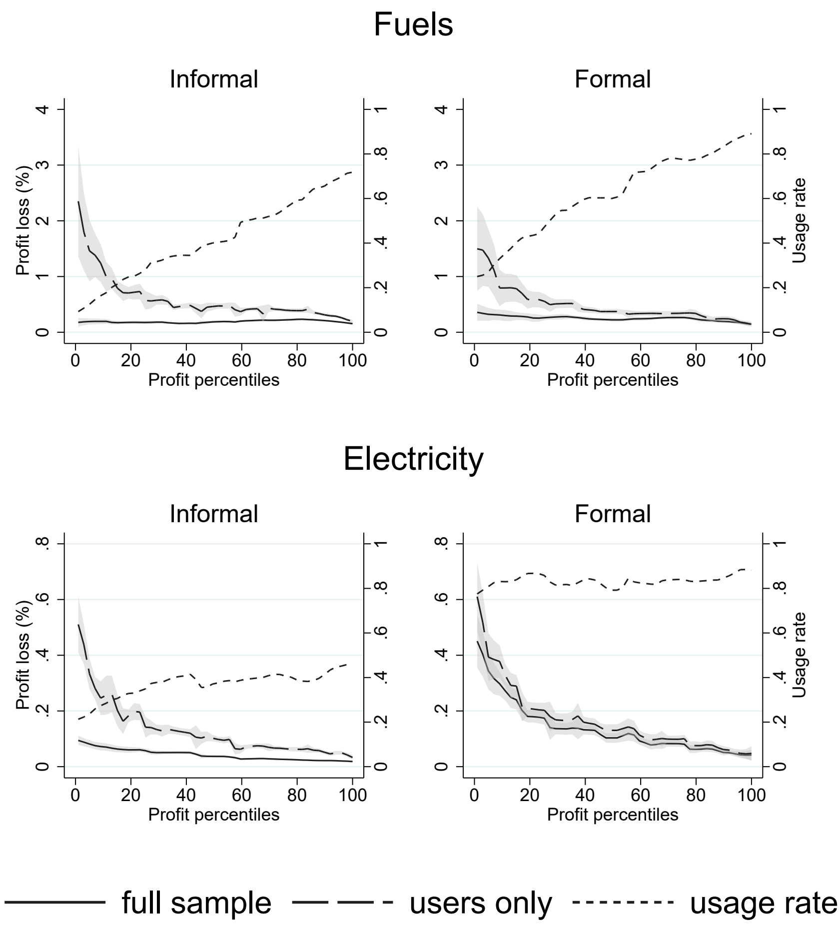


Figure 2.3: FO estimates, formal versus informal firms

Figure 2.3 shows the incidence of estimated FO effects as well as the average energy usage rate across profit percentiles, separated into formal and informal firms. The incidence curves of FO effects of fuel price increases are similar for both types of firms. The usage rate is slightly lower among informal firms, and FO estimates for users higher, especially at the bottom of the profit distribution. We observe significant differences for electricity price increases however. Since the usage rate of electricity is constant at a very high level among formal firms (on average, around 83 percent of them use electricity), the incidence of FO estimates for the full and users-only sample are similar across the whole profit distribution. Moreover, both average and users-only FO estimates are higher for formal firms. Hence, the latter are more heavily affected by electricity price increases because more formal firms use electricity, including those that operate with small profit margins.

2.4.2 Elasticity estimates

Table 2.3 shows own- as well as cross-price elasticities of input-demand for MSEs with hired labor and for the self-employed in all industries.[11] MSEs react to fuel price increases by increasing labor input rather than electricity input quantities, as the cross-price elasticities for fuels and electricity are not significantly different from zero. Fuels exhibit the highest responsiveness to price increases. Among firms using hired labor, the fuel quantity falls by an average of 0.84 percent for a 1 percent price increase (compared to 0.45 and 0.37 percent for electricity and labor respectively). When fuel (electricity) prices rise by 1 percent, the quantity of labor employed goes up by 0.28 (0.09) percent on average. By way of comparison, studies of European firms have found labor elasticities with respect to energy of 0.07 for Italian manufacturing firms (Bardazzi et al., 2015) and 0.01 for Irish manufacturing firms (Haller and Hyland, 2014). We observe a larger increase in quantities of fuels and electricity employed in production when wage rates rise – namely 0.78 and 0.59 percent respectively – for a 1 percent price increase. This is reasonable since – as long as no new equipment is required – energy inputs can be adjusted more flexibly than labor.

Table 2.3: Own- and cross-price input-demand elasticities

	Price of fuels	Price of electr.	Price of labor
Firms with hired labor			
Fuels	-0.84***	-0.04	0.78***
Electricity	-0.09	-0.45***	0.59***
Hired labor	0.28***	0.09***	-0.37***
Self-employed			
Fuels	-1.15***	0.06	0.53***
Electricity	0.12	-0.41***	0.32***
Own labor	0.07***	0.02***	-0.09***

Notes: Significance levels: * p<0.1, ** p<0.05 *** p<0.01. T-statistics and resulting significance levels are computed using the delta method. Elasticity estimates are obtained after the fourth iteration for hired labor and after the tenth for one-person firms. This reduced the sample size from 2,973 to 1,758 and from 4,303 to 1,363 respectively. The labor-energy cross-price elasticities remained fairly close to the first estimations (maximum magnitude change is 0.3 in point estimates).

For the sample of one-person firms, we include own-labor input at shadow wages, approximated by regional average wages computed from the survey. These entrepreneurs may have less capacity to adapt to rising energy prices than firms employing workers. Indeed, we find

[11] Note again that these elasticities are estimated for a subsample of firms that use both fuels and electricity.

higher own-price elasticities of both energy goods and comparatively small energy-labor cross-price elasticities. Firm owners increase their labor supply to the firm by only 0.07 percent as a response to a 1 percent fuel price increase – compared to 0.28 percent for firms that hire labor.

The presented elasticities are average estimates for all industries. It is more common to estimate a cost-function for a less diverse sample of firms due to differing production technologies, which can imply different own- and cross-price elasticities. When estimating the model for the manufacturing, service, trade, as well as restaurant and hotel industries separately, elasticity estimates differ slightly for some cases.[12]

Table 2.4 presents elasticity estimates for both formal and informal firms. Probably contrary to expectations, we find no differences in reactions to price increases based on that status for either the self-employed or for firms with hired labor. However, this result may partly reflect selection in the subsample of firms that use both fuel and electricity. Among informal firms, about 17 percent use both types of energy, compared to about 49 percent of formal firms. These two subsets of firms thus react similarly to energy or labor price shocks. The following simulation of SO profit losses — which again only covers those firms that use both energy types -– therefore does not distinguish between formal and informal firms.

2.4.3 Second-order profit losses

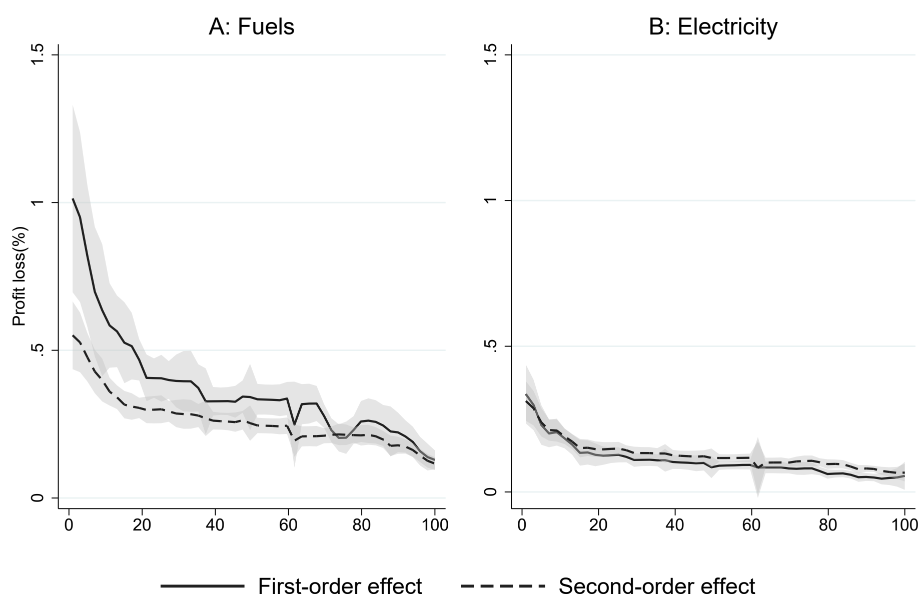


Figure 2.4: FO and SO estimates for a 1 percent price increase for firms with workers

Figure 2.4 shows both first- and second-order effects of a 1 percent price increase at per-

[12]See Tables A2.2–A2.5 in Appendix D for elasticities by industry. For example, the labor demand elasticity with respect to fuel prices ranges between 0.22 and 0.32 for large firms and from 0.05 to 0.09 for one-person firms.

Table 2.4: Own- and cross-price input-demand elasticities, formal versus informal firms

Formal firms	Price of fuels	Price of electr.	Price of labor
Firms with hired labor			
Fuels	-0.83***	-0.05*	0.79***
Electricity	-0.12*	-0.45***	0.63***
Hired labor	0.28***	0.10***	-0.37***
Self-employed			
Fuels	-1.12***	0.02	0.84***
Electricity	0.04	-0.44***	0.43***
Own labor	0.10***	0.02***	-0.12***
Informal firms	**Price of fuels**	**Price of electr.**	**Price of labor**
Firms with hired labor			
Fuels	-0.81***	-0.04	0.76***
Electricity	-0.09	-0.41***	0.50***
Hired labor	0.30***	0.08***	-0.38***
Self-employed			
Fuels	-1.15***	0.06	0.53***
Electricity	0.12	-0.41***	0.32***
Own labor	0.07***	0.02***	-0.09***

Notes: Significance levels: * p<0.1, ** p<0.05 *** p<0.01. T-statistics and resulting significance levels are computed using the delta method. Elasticity estimates are obtained after the fifth iteration for formal hired labor and after the eighth for formal one-person firms. This reduced the sample size from 2,143 to 1,391 and from 2,266 to 1,024 respectively. Elasticity estimates for informal firms obtained after the ninth iteration for hired labor and after the eighth for one-person firms. This reduced the sample size from 830 to 436 and from 2,266 to 1,024 respectively.

centiles of the profit distribution for the sample containing firms with workers that use both fuels and electricity. The difference between first- and second-order estimates of profit losses is moderate for most firms with hired labor. When fuel prices increase, the bottom 10 percent of firms mitigate up to 35 percent of the losses by hiring more labor (panel A). On average, the SO effect is 21 percent lower than the FO one for fuel price increases. Yet, even when accounting for behavioral adjustments on the input side, average profits for firms with hired labor still decrease by 0.31 percent – and by more than 0.53 percent for the bottom 10 percent – in the case of a 1 percent increase in fuel prices. For electricity, the profit loss is about 0.12 percent on average, with little difference between first- and second-order effects (panel B).

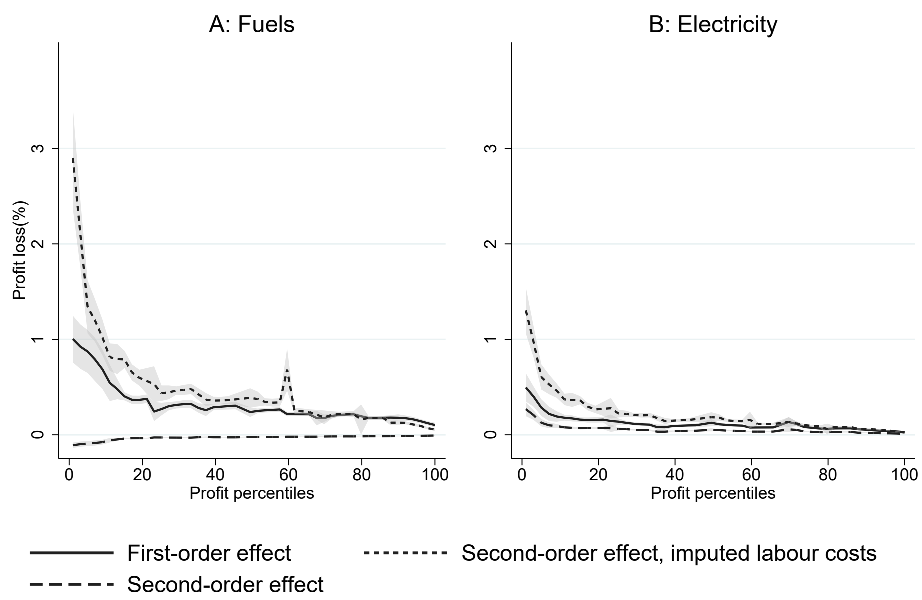


Figure 2.5: FO and SO estimates for a 1 percent price increase for firms without workers

For one-person firms that use both fuel and electricity, we see a stark difference between first- and second-order estimates, particularly for fuel price increases (Figure 2.5, panel A). The profit loss reduces to zero for fuel (and close to zero for electricity) across the whole distribution. As the elasticity estimates indicated, these firms shift away from electricity or fuel in almost exact proportion to the price increase and they substitute own-labor supply for energy. As this increase in own-labor supply does not cause direct and observable monetary losses, we compute an estimated profit loss assuming that the owner would pay himself or herself the prevailing regional average wage – only for the additional labor input. Shadow wages for the self-employed are likely to be very heterogenous and, probably, lower on average than the average regional wage. Further inquiry into shadow wages goes beyond our paper, but the results of this exercise have to be interpreted with caution. Under this assumption, the loss due to fuel or electricity price increases is almost twice as large as the FO effect on average, with entrepreneurs at the low end of the profit spectrum being particularly affected. This holds for both fuel and electricity. The profit losses associated with electricity price increases are somewhat more pronounced for one-person firms compared to those with hired labor. The average FO effect is around 0.22 percent for a 1 percent price increase, while the SO effect is about half as big.

These results on SO effects show that the relatively strong behavioral reactions tend to mitigate negative impacts on profits for the self-employed. These entrepreneurs raise their own labor supply. Although the costs of doing this are difficult to quantify precisely, considering imputed additional labor costs suggests that they are substantial. For larger firms with employees, behavioral adjustments are also important for fuels, but not for electricity.

2.4.4 Output prices

To test whether MSEs pass on fuel price increases, we now regress unit output prices on fuel prices, both normalized using the national producer price index (excluding oil).[13] We focus on fuels because both direct and (expected) indirect effects are larger than for electricity price increases. Most important for this empirical analysis is a sufficiently large number of producers of the same products in our sample. To maintain statistical power, we set the cutoff point for observations per product and year to 50. This leaves producers of tortillas, tacos, and tamales in the estimation sample.[14] These products are supposedly of similar quality across producers and time. Hence, unobserved differences in product quality are expected to be small. Since tortilla prices were from time to time regulated in Mexico (see e.g. Barrera, 2007), we show two sets of regression results: one using a sample including tortilla producers and one excluding them respectively.

Table 2.5: OLS regression results for price transmission

Dependent variable:	Log(unit output price/PPI)					
	Including tortilla producers			Excluding tortilla producers		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(fuel price/PPI)	0.717***	0.741***	0.734***	0.822***	0.889***	0.955***
	(0.204)	(0.174)	(0.185)	(0.296)	(0.262)	(0.275)
Observations	1,389	1,389	1,311	708	708	670
Adjusted R-squared	0.657	0.742	0.738	0.01	0.251	0.254
Product-unit FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE		Yes	Yes		Yes	Yes
Firm characteristics^x			Yes			Yes

Notes: FE = fixed effects; PPI = producer price index. Significance levels: * p<0.1, ** p<0.05 *** p<0.01. Robust standard errors in parentheses. Intercept included but not reported. ^{x}Firm characteristics include one-person firm (dummy), age and years of education of the entrepreneur, and age of the establishment. Status of informality excluded due to data gaps in the ENAMIN 2008 survey.

Table 2.5 shows the regression results for different specifications. In columns (1) and (4), we control for product type and unit to control for self-induced spurious correlation, while in columns (2) and (5) we add state fixed effects, and in columns (3) and (6) firm-level controls

[13] Remember that we can pool the surveys of 2008, 2010, and 2012 for this analysis.

[14] Further lowering the cutoff value would for example include producers of blouses, doors and hammocks. Since these items can be produced with marked differences in quality, we expect significant heterogeneity in product prices due to unobserved differences in product quality. Unfortunately we do not have panel data, so we cannot control for firm-product fixed effects (which would capture differences in quality to some extent). We therefore do not include these in our estimation sample.

respectively. In the sample including tortilla producers, a gasoline price increase of 1 percent (relative to the general price level) leads to a rise of about 0.72–0.74 percent in unit output price (relative to the general price level). The estimated price elasticity is even larger when excluding tortilla producers, at around 0.82-0.96. This is a sizeable effect, and indicative that at least the firms in the selected sectors are able to deal with rising fuel prices by increasing output prices. Again, note that this estimate reflects not only the reaction to fuel prices but also to fuel-price induced price increases in transportation costs and intermediate input prices. The inclusion of firm characteristics leaves the elasticity estimate unchanged.

To put these reactions into perspective, we compute FO profit loss estimates of a 1 percent price increase for firms in the estimation sample used here (including tortilla producers). This loss is estimated at 0.45 percent for a 1 percent fuel price increase in 2012 (N=483).[15] To compensate for this loss, output prices would need to change by the exactly the same percentage, given that there are negligible economies of scale (marginal cost does not depend on quantity produced in the vicinity of current production levels). Thus, according to the estimated output price elasticities, firms more than compensate for the estimated direct profit loss. This indicates that the full (direct plus indirect) cost increase is – either wholly or to a large extent – passed on to consumers. It is nevertheless possible that some firms absorb parts of the price increase initially, especially those with larger profit margins.[16]

2.5 Conclusion

This paper is the first to provide evidence on the considerable impact of energy price increases on small firms in developing countries using a representative dataset of both formal and informal micro- and small-sized enterprises from Mexico. We find sizable potential effects. Our estimates of first-order effects indicate that a 20 percent increase in fuel prices – as previously once experienced in Mexico in the course of a single week – can translate into an average 4 percent direct profit loss for MSEs if they are unable to adjust. The effects of fuel price changes are much more pronounced than those of electricity ones, reflecting higher cost shares of fuels.

Examining these potential immediate effects by industry, we detect notable differences. The effects extend well beyond the transport sector, where fuels account for about 56 percent of total costs. While fuel and electricity use are correlated with higher profits, it is the fuel- and/or electricity-using firms at the bottom of the profit distribution that are affected most by energy price increases. For them, a fuel price increase of 1 percent can cause profits to decline by even more than 1 percent, as a result of low profit margins in combination with high fuel cost shares.

[15] SO profit loss estimates are only available for firms with positive expenditures on both fuels and electricity: they stand at 0.09 percent, down from 0.68 percent (N=151).

[16] Figure A2.2 in Appendix E illustrates that FO profit loss estimates are below the point estimate of the price transmission, but within the range of the 95% confidence interval.

The average direct impact of fuel price increases on formal firms is larger than for informal ones (0.25 versus 0.19 percent respectively for a 1 percent price increase), as the former use fuels more often. The same holds for electricity. The somewhat higher profit margins of formal firms thus cannot protect against higher losses due to a greater share of energy costs.

The FO effects should be interpreted as very short-term and immediate ones that will be quickly followed by adjustments on the part of firms, and by increases in intermediate input prices. We believe these effects still important and informative from a political economy perspective, as they play a role in how potential losses arising from price reforms are perceived. However, as noted, firms do adjust. Our analysis of behavioral reactions shows that even though larger (but still small) firms with hired workers are able to reduce fuel consumption somewhat, their profits decrease by 0.27 percent in response to a 1 percent fuel price increase. Behavioral reactions to fuel price increases are particularly strong for one-person firms that respond to the price shock by increasing their labor supply. Thus the negative impacts on profits are mitigated, but including the 'shadow' costs of a higher own-labor supply would probably leave many entrepreneurs worse off. Somewhat unexpectedly, we find no behavioral differences between formal and informal firms. However this is true in subsamples that only include firms that use both fuels and electricity for production, which is more often the case with formal ones.

The indicative computations of the second-order effects rest on the assumption that MSEs are cost-minimizing, choose to maintain production levels, change labor demand only at the intensive margin, and do not pass on prices. Given the large simulated profit losses, however, entrepreneurs may well choose to change the type of activity, search for other employment opportunities, or increase output prices. We find evidence of relatively large output price elasticities with respect to fuel prices for food-processing firms compensating for estimated profit losses. This suggests that at least some MSEs adjust to fuel price increases by increasing output prices, a claim corroborated by news reports following the *gasolinazo* (Gonzalez, 2017).

The results of our analysis call for policy measures that mitigate the effects of energy price policies, whether in the context of fossil fuel subsidy reform or of the introduction of carbon taxes. While we expect general welfare gains from, for example, subsidy removals, we show that the immediate impact on the profits of small firms can be – and is likely to be perceived as – substantial for both formal and informal small firms. We thus propose increasing transfers to poor households and linking them explicitly to the implemented energy price policy, thus potentially increasing political support for fossil fuel subsidy removal or carbon pricing. Ideally, such transfers would be temporary, particularly as our analysis suggests that even small firms have the capacity to adjust. Despite the heterogeneity in impacts, we consider lump-sum transfers likely to be more efficient than more targeted compensation measures (for example, toward certain sectors) in light of the multiple adjustments by firms – including input substitution and output price changes. The financial means are often there: in Mexico, not long ago, energy subsidies amounted to 10 times the budget of "Prospera" (formerly "Oportunidades"), the main transfer program in the country (Andretta, 2011).

Chapter 3

Energy prices, generators, and the performance of manufacturing firms: Evidence from Indonesia

3.1 Introduction

Ever since the introduction of energy into modern day production processes, energy price fluctuations have been a primary concern due to their negative economic consequences (Kilian, 2008). For high income countries, the oil crisis of the 1970s was the first serious economic recession to be attributed to an increase in energy prices, which has left a lasting impression in the assessment of energy price shocks to this day. With evidence of global warming and the implemented and planned policies to reduce greenhouse gas emissions from fossil fuels, there is now a renewed interest in energy price changes and their economic effects (Parry et al., 2021).

For industrialized countries, recent empirical studies document no or negligible short-term effects of carbon pricing on firm productivity, partly because the energy price increases have been relatively small until now (see Venmans et al., 2020, for a recent overview). Rising emission prices caused by the cap-and-trade scheme reduced emissions of firms in France, Netherlands, Norway, and the United Kingdom by around 10 percent, without affecting firm performance (Dechezlepretre et al., 2018). French firms, for instance, achieved such emission reductions through targeted investment instead of production (Colmer et al., 2020).

Evidence on the impact of rising energy prices on firm performance and emission intensity in emerging or developing countries, however, is relatively scarce. Exploiting exogenous variation in electricity prices, Abeberese (2017) shows that Indian firms adopt less electricity

This is joint work with Krisztina Kis-Katos and Sebastian Renner.

intensive production processes, but also lower their output and productivity growth rates and decrease their machine intensity.[1] In low- and middle income countries, firm performance is also closely related to the reliability of electricity. Due to the large demand that exceeds the capacity of an imperfect energy supply infrastructure, the resulting power outages lead to considerable productivity losses (Abeberese et al., 2019; Cole et al., 2018; Allcott et al., 2016; Fisher-Vanden et al., 2015).

In developing countries, firms often respond to the unreliable electricity grid by operating their own electricity generators, usually fueled by diesel (Alby et al., 2012). Such firms will react differently to relative price increases of fuels due to their past technology choices. Widespread generator use, although economically beneficial in the short run, poses challenges for sustainable development. Generator-using firms have a higher cost-share of fuels in general and rely on more energy and emission intensive production processes. Understanding how these firms respond to energy price increases is therefore particularly important for the success of energy and climate policies.

We address this empirical gap by using a large panel data set on medium-size and large manufacturing firms in Indonesia, based on yearly balance sheet data. We exploit policy-induced variation in energy tariffs from 2000 to 2015 to examine the differential impact of fuel price increases on the performance of firms that have previously used a generator for electricity generation, in comparison to similar (matched) firms that have not been using a generator before. We identify differential firm responses to rising fuel prices conditional on firm fixed effects as well as electricity tariff changes, but also controlling for a wide range of location-specific shocks (including district-year effects) and product-specific fluctuations in demand and supply factors (relying on product-year effects at the 5-digit level). We estimate the impact of fuel price increases on firms' output, value added, productivity, and input use as well as their energy and emission intensities to examine the extent of emission reduction due to potential dis-adoption of generator use. This is especially relevant for Indonesia, which was among the 10 largest emitters of carbon dioxide worldwide in 2020 (Global Carbon Atlas, 2022).[2]

We find that diesel tariff increases causes some firms to dis-adopt generators. Further, they affect firms that have been reliant on generator use in the past differently: total output, value added, labor and material inputs decline relative to firms not using generators. This is likely due to a combination of generator dis-adoption and higher costs of self-generated electricity. We further find that firms adjust labor demand flexbily, thereby preventing productivity losses. Even though generator use is associated with higher energy and emission intensities of produc-

[1] For a contrasting view, Calì et al. (2022) describe a positive association between fuel price increases and firm performance in Mexico and Indonesia.

[2] Per capita emissions in Indonesia, excluding those from land-use change and forestry (LUCF), are relatively low. However, being the fourth most populous country in the world, even small rates of energy demand growth per capita lead to a relatively large absolute increase in carbon dioxide emissions.

tion, we do not find any evidence for a differential effect on these intensities. Our findings have implications for energy price policy in developing countries when both maintaining competitiveness of the manufacturing sector and emission abatement is a priority.

This paper proceeds as follows: Section 2 provides an overview of data sources, energy price policy and generator use in Indonesia, and derives empirical hypotheses. Section 3 describes the empirical model. Estimation results are presented and discussed in Section 4, while Section 5 concludes.

3.2 Data and hypotheses

3.2.1 Data sources

We use *Survei Industri (SI)*, the annual manufacturing census of medium size and large manufacturing establishments that employ at least 20 workers, conducted by Statistics Indonesia (Badan Pusat Statistik, BPS). This census records basic balance sheet information for each firm and includes a series of questions on energy usage and related expenditures. We link the yearly survey rounds into a panel of manufacturing establishments over 18 years (1998 to 2015) with a total number of observations of around 420,000. The data is separately recorded for each plant and no ownership linkages between plants are recorded; for the sake of simplicity, we refer to all establishments as firms.

Fuel tariff data are obtained from several different sources (Chelminski, 2018; Husar and Kitt, 2016; Kojima, 2016; Beaton and Lonton, 2010). Electricity tariff data for 2000 to 2015 combines information provided to us by the Jakarta office of the national electricity company, PLN (*Perusahaan Listrik Negara*).[3] We obtain information on electricity generation (2000–2015) and province-level grid quality indicators (2010–2015) from Handbooks of Energy and Economic Statistics in Indonesia (e.g. Ministry Of Energy and Mineral Resources, 2017), and several statistical handbooks published by the PLN (*Statistik Listrik PLN*). Using information on electricity generation, we estimate the energy content of one kWh of electricity produced or distributed by PLN using the tier 1-method proposed by IPCC (2006) (see Section 5.8 for details).

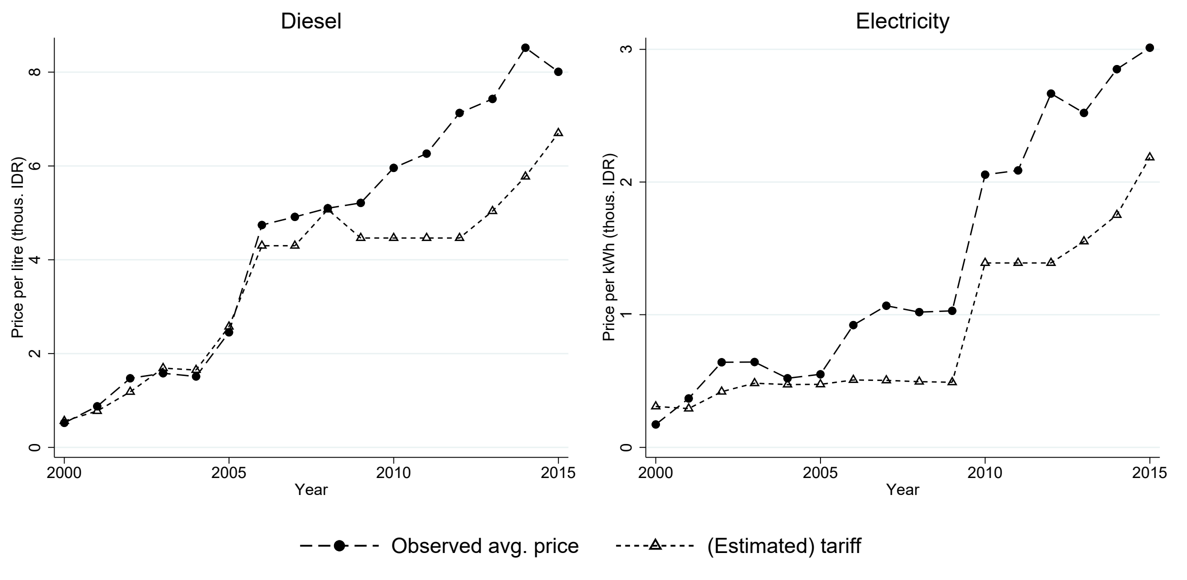
3.2.2 Energy prices

For our empirical analyses, we exploit price variation that stems from changes in Indonesia's fossil fuel subsidy system, as well as from the national price policy of PLN. We argue that most

[3]PLN is a government-owned corporation that is responsible for the major share of electricity generation and its distribution. It produces around three-quarters of the total electricity distributed by it, while another 22% are provided by independent power producers via purchase agreements with PLN (IEA, 2015).

tariff adjustments are plausibly exogenous to firm performance.

Fuel tariff policies and observed fuel prices In 2004, Indonesia's oil imports exceeded its oil exports for the first time since it started oil production. This led to an explosive growth in the fiscal cost of fuel subsidies, amounting to 24% of the government expenditures. The resulting fiscal pressure was the major cause of tariff increases by over 100% for diesel and gasoline in 2005, which were introduced despite a wide opposition to these reforms (Chelminski, 2018). The observed average diesel prices are closely aligned with official tariff rates (see the left panel in Figure 3.1). Since fuel tariffs were raised in opposition to interest groups and on the basis of fiscal concerns, the changes in the Indonesian tariff policies left relatively little possibility for endogenous response of policy makers to firm performance measures and affected all firms alike. Changes in the official tariff rates were closely mirrored in the black market price of fossil fuels (Chelminski, 2018), as indicated by the close alignment of official tariffs and observed average prices in the firm census.



Notes: Estimated electricity tariff per kWh combines monthly load fee (fixed until 2010) and average variable tariff, it does not include k-factor, and is an average of tariffs I-2, I-3, and I-4.

Figure 3.1: Diesel and electricity prices and tariffs, 2000–2015

Electricity tariffs and their reform The Indonesian government is also responsible for setting electricity tariffs as the parliament gives final approval to tariff changes. Industrial customers are classified into four tariff categories based on the electric power of their electricity demand: category 1 includes firms with an electric power demand of 0.45–14 kVA, category 2 refers to 14–200 kVA, category 3 to 200–30,000 kVA, and category 4 to higher power demand. As electric power is the product of the electric potential of the power connection and the electric current, the type of power connection and the amount of electricity needed to power all machinery will determine the tariff group of each firm, whereby larger firms typically belong in higher tariff categories. The right panel of Figure 3.1 depicts the average variable electricity tariff by taking a simple average over the tariff categories 2 to 4, excluding category 1 that applies to small-scale customers. It also depicts an estimated average electricity price, which adds a second load fee on top of the variable component. Until 2010, the value of the monthly load fee was fixed and electricity prices remained fairly constant. In 2009, the electricity tariff system underwent substantial reform which led to stark tariff increases in 2010. The reason for reform were again fiscal issues: Revenue from the sale of electricity covered only half of the total cost of production in 2009, and government subsidies provided to PLN were not able to fill this gap (Mourougane, 2010). For all firms in categories 2 to 4, the fixed monthly load fee was exchanged for a variable fee, dependent upon energy consumption in kWh. This led to a sharp increase in the effective electricity tariffs, and decoupled the marginal price of electricity from consumed quantities. In subsequent years, the tariff was regularly raised.

Observed electricity prices In the yearly census, firms report both the quantity and the total costs of their electricity usage within each year, from which we can derive the average electricity price observe by each firm (Figure 3.1). As we lack firm-specific information on the tariff categories each firms belongs to, for our subsequent analyses we will rely on average electricity tariffs. Figure 3.1 shows that the average electricity price reported by the firms is higher than the electricity price estimated from official tariff rates in almost all years. This is mainly due to peak pricing as in times of high electricity demand, PLN applies an additional load factor that lies between 1.4 and 2. Overall, tariff increases are well reflected in observed prices.[4]

Correlation between tariffs and observed prices Table 3.1 reports results from regressing the observed fuel and electricity prices on the respective tariffs within our firm panel. The average diesel and gasoline prices reported by the firms are very closely correlated with the respective fuel tariffs, with a nearly unitary elasticity and high R-squared values above 0.9, both when excluding and including firm fixed effects. To compare electricity prices, we regress the electricity prices reported by the firms on our estimate of the average electricity tariff. For the period of 2000 to 2009, we use the average tariff rate instead of the estimated electricity price per firm as the latter is mechanically influenced by the quantity consumed in this period due to the fixed monthly fee component. Results show that reported electricity prices are less strongly

[4]As we cannot precisely link firms to tariff categories, we compute an average yearly tariff by taking a simple average over the tariff categories 2 to 4, excluding category 1 that applies to small-scale customers. Figure A3.1 in the appendix confirms that average tariffs depict tariff movements well also within the separate tariff categories. Tariff adjustments are highly correlated across categories, except in 2015, when the variable tariff for larger customers (categories 3 and 4) increased sharply, while the tariff for customers in category 2 remained constant.

Table 3.1: Do tariffs predict prices? OLS regression results

	log Diesel price		*log* Gasoline price		*log* Electr. price	
	(1)	(2)	(3)	(4)	(5)	(6)
log Tariff rate	1.111***	1.094***	1.072***	1.051***	1.529***	1.355***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.029)	(0.025)
Observations	227,737	218,686	184,675	174,721	315,699	306,146
Adjusted R-squared	0.912	0.914	0.900	0.906	0.279	0.406
Firm FE	No	Yes	No	Yes	No	Yes

Notes: Standard errors clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1. Energy prices are trimmed at the 1st and 99th percentiles.

correlated with average electricity tariffs, with elasticities of around 1.3 to 1.5, and substantially lower adjusted R-squared values. This latter result confirms that our estimated electricity tariffs are subject to somewhat more imprecision due to our use of average tariffs instead of category-specific tariffs as well as the unaccounted for role of peak pricing and tariffs for excess reactive power usage. Nonetheless, the correlation between actual and average market prices is still substantial. In our statistical analyses, we will rely on the more exogenous average market tariff measures as explanatory factors that are not affected by firm-specific demand fluctuations.

Trends in grid quality The system average interruption duration index (SAIDI) is the average time of power failure per customer, an important indicator of grid reliability. Figure 3.2 plots the average country-wide SAIDI index, as well SAIDI indices for selected four provinces on Java for the years 2010 to 2015 (the only years for which regional data are available). Three observations stand out: In 2010, the year of the largest electricity price increases, country-wide grid quality improved dramatically compared to the years before. Second, substantial regional variation exists. Third, at the regional level, year-to-year variation in grid quality is larger compared to the year-to-year variation of the national average.

3.2.3 Generator use

Economic determinants of generator use We expect firms to decide to invest into a generator based on a cost-benefit calculation (Alby et al., 2012). The benefits from generator adoption depend crucially on the quality of electricity supply and increase with the frequency and duration of blackouts. The benefits are largest in sectors that are more reliant on the quality of electricity supply in their production process. Finally, if the size of firms (or their net worth) is indicative of the credit constraints they face, larger firms will find it easier to invest into generators. Based on these assumptions, Alby et al. (2012) predict that power outages will affect

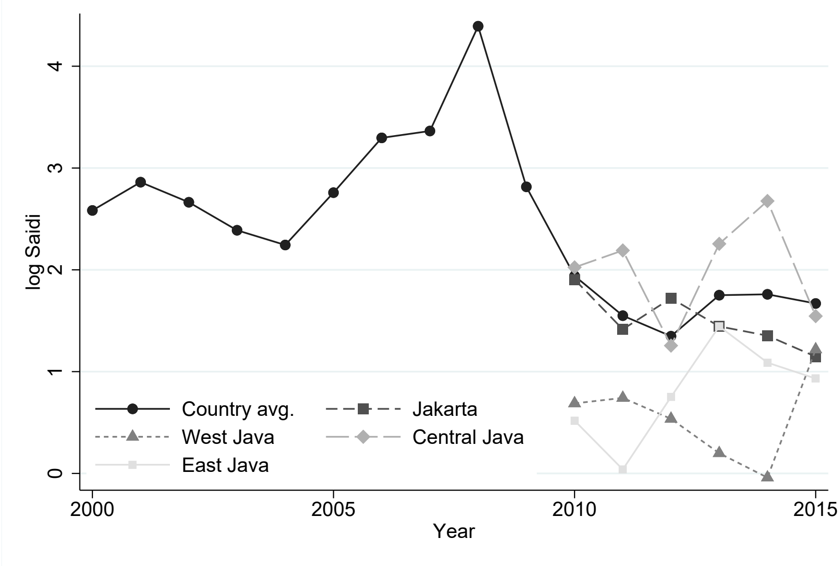
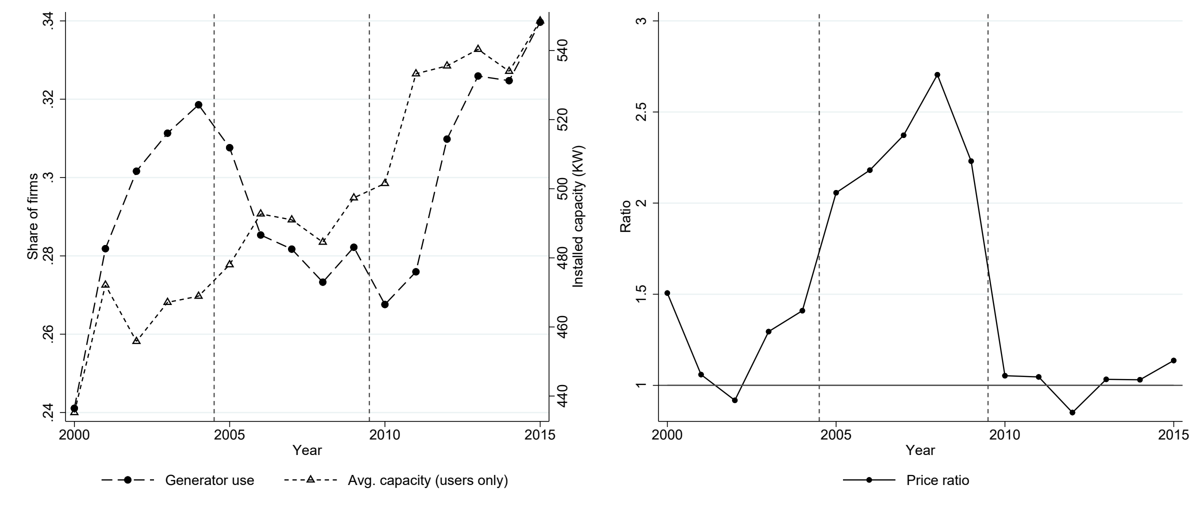


Figure 3.2: Saidi index, 2000–2015

especially smaller firms that operate in sectors with a high electricity sensitivity. If smaller firms cannot afford to invest in generators, they will either exit such a market or do not enter it to begin with. Generator adoption will also be influenced by the relative price difference between fuels and electricity, which will affect the expected net returns of generator use. Increasing relative electricity prices, as observed in Indonesia especially after 2010, will spur on generator adoption. Firms that have made this investment decision in the past, will consider the costs of continuing to operate a generator. Increasing fuel prices relative to electricity prices (as observed from 2005 to 2010 in Indonesia) can be expected to lead to generator dis-adoption but also economic losses and possibly even market exit of smaller energy-reliant firms.

Characteristics of generator using firms In the firm census, we observe whether a firm used generators in a given year, the number of generators used, as well as the total installed capacity. Firms that use generators are indeed on average larger in terms of their capital stock, number of workers, total sales and value added, and more productive in terms of value added per worker (see Table A3.1 in the appendix for a range of summary statistics). Generator using firms are also more energy intensive per monetary unit of value added (by around 60%), and are somewhat more often found in electricity sensitive sectors as defined by Alby et al. (2012), that is, those sectors in which firms are above the median electricity cost share. Their emission intensity is also around 60% higher on average. Comparing similarly-sized firms operating in the same 5-digit-sector to each other, we observe that those with generators are about 20–22% more energy and emission intensive (see Appendix B for details on the computation of energy and emissions intensity). Hence, the use of generators is associated with increased emissions per kWh of produced electricity solely due to the fact that electricity generators have a comparatively low energy conversion efficiency compared to grid electricity production.

Dynamics of generator usage in Indonesia Figure 3.3, left panel, shows that ownership rates and average installed capacity closely follow the price movements described above. The right panel shows the price ratio between estimated self-generated and grid electricity.[5] The share of firms that use generators drops after the stark fuel price increases in late 2005 (left panel), which drove up prices of self-generated electricity relative to grid electricity, which were then more than twice as large (right panel). Simultaneously, the average installed capacity increases, which reflects selection effects as firms that own fewer generators stop using them. Starting in 2010, when electricity tariffs were adjusted upwards, the price ratio between self-generated and grid electricity sank to around one – and both the share of firms that own generators, as well as average installed capacity rose.



Notes: The left panel of this figure contrasts the share of generator using firms in the census over time with average installed capacity per user in kW. The right panel shows the estimated price ratio of self-generated electricity versus grid electricity (P_{self}/P_{grid}). Vertical lines mark the years before the major diesel fuel (2005) and electricity tariff (2010) reforms. Source: SI.

Figure 3.3: Trends in generator use and capacity, and price ratio of self-generated electricity versus grid electricity, 2000–2015

This direct price comparison illustrates that investments in a generator became relatively more attractive to firms after the electricity tariff adjustment based on price considerations alone. However, note that the estimated cost range for generators does not include costs for lubricants, maintenance, or initial investments. Hence, the true average variable costs of one kWH produced by generators were likely a little higher than the costs for grid electricity even

[5]Figure A3.2 in the appendix compares in more detail the average observed grid electricity cost per kWh with the estimated variable price range per kWH produced by generators (only including diesel fuel as input cost factor).

after 2011. Even though the share of firms that use a generator increased after 2010, generators have become less important for electricity production: The average share of self-generated electricity among generator-using firms decreased from about 49 percent in 2000 to about 33 percent in 2015. This is probably due to a combination of high fuel prices (which makes self-generated electricity more expensive) and improvements in grid quality (attenuating the need to use generators during blackouts).

3.2.4 Empirical hypotheses

Imperfect pass-through of prices The recent empirical literature provides only scarce evidence on the transmission channels from energy prices to firm performance. In general, firms are unlikely to completely pass through higher energy prices to final demand. Ganapati et al. (2020) estimate pass-through rates of around 70% and Hintermann et al. (2020) of 35 to 60% for selected US and German manufacturing sectors respectively. There are no estimates available for middle income countries, and estimation for Indonesia is infeasible due to the absence of credibly exogenous price variation. However, we assume that firms in Indonesia can also pass forward energy prices only imperfectly. Firms are therefore facing losses in value added if they do not respond to price increases. A natural adjustment channel is to invest in more energy-efficient capital and reduce energy use in production (Berndt and Wood, 1975). Another option is the diversification of the production portfolio to less energy-intensive products (Abeberese, 2017).

Differential price effects by generator ownership We add to these considerations another important determinant of a firm's response to energy price increases: its previous investments in generators. Firms that rely on generators for parts of their electricity supply are likely to have a higher energy intensity due to the comparably low efficiency of generators, and have higher cost shares of fossil fuels compared to firms not relying on generators. Hence, these firms face larger potential cost increases due to fuel price increases, which leads to a competitive disadvantage. Both fuel and electricity price changes affect a firm's decisions to demand and supply electricity, and will thus also affect its decision to start, continue, or stop using a generator. Stopping generator use due to fuel price increases might disrupt the production process, especially if the grid electricity supply is either unreliable or insufficient to support production at capacity limit.

Adjustments after fuel vs. electricity price increases In the short run, fuel price increases will reduce generator using firms value added relative to other firms if they fully absorb this price shock. Negative production volume and productivity effects can arise if generator using firms shift their energy use towards the less reliable grid electricity, which results in more frequent disruption of production and can potentially cause a downscale of production volumes.

In case labor inputs cannot be adjusted fully flexibly, we expect further negative impacts on productivity. Investments in more energy efficient technology, by contrast, might increase productivity in the medium run. In this paper, we focus on the short-term impacts, however. By contrast, the expected effect of electricity price increases is more ambiguous. When electricity from the grid becomes more expensive, this increases the profitability of self-generated electricity. In case firms with previous generator investments can increase the share of self-produced electricity more easily, so that firms that already produce large shares of electricity themselves will suffer relatively lower cost increases than firms that before only used to buy electricity from the grid. However, new firms opting into generator usage due to the electricity price hikes may also catch up with firms with previous generator use in terms of their production capacity and productivity. This is because firms that adopt generators not only potentially save on grid electricity costs, but also obtain the possibility of maintaining production during blackouts. Unfortunately, due to data constraints concerning regional grid quality, we cannot credibly estimate the differential impact of electricity price increases.

Regional grid quality as unobserved factor Changes in electricity grid quality will also likely affect generator-using firms differently than firms not using any generator. Generator reliant firms benefit less from improvements in grid quality, which reduce interruptions in production due to fewer blackouts relatively more among those firms that rely solely on the grid. In our empirical model, we will only be able to control for improvements in grid quality at the national level due to incomplete regional data. Since variation in grid quality will affect generator-using firms differently than firms not using generators, our impact estimates will be biased by the omission of an interaction term between regional grid-quality and a generator reliance measure. We think that the bias arising from this omission will be larger during the period 2009–2015, since the improvement in average, country-wide grid quality is correlated with the electricity tariff increases in that period. Hence, we do not report estimates of the differential effect of electricity price increases, even though we control for them in our empirical model.

3.3 Estimation strategy

Our empirical model compares the effects of fuel price increases in two different groups of firms, those relying on generators and those not. The tariff increases affect all firms simultaneously, and thus their effects cannot be distinguished from a whole range of common policy shocks and macroeconomic fluctuations, which are captured by year fixed effects in our models. Once year fixed effects are included, we cannot estimate the average effect of tariff increases on firm performance. Interactions terms between tariffs and other firm-level variables, however, are highly informative and can still be estimated. More specifically, previous investment decisions into electricity generating technologies will affect how firms adjust to such price changes. For instance, descriptive trends in Figure 3.3 show that with the stark price increase in 2005, the share of firms with generator ownership declined substantially, and increased again with electricity tariff increases.

As generator ownership may directly respond to price increases in year t, our main analysis builds a measure of generator reliance in the past. We proxy for generator reliance by past generator ownership G_{isd0}, which is an indicator variable that takes the value of one if a firm has reported using a generator at least once during 2000 – 2004. This period was characterized by relatively stable energy prices, and thus the decision to invest in a generator should not have been influenced by price changes. To address the differential effects of fuel tariff increases by former generator reliance, we interact a measure of past generator ownership with current prices of diesel fuel, D_t, and electricity, E_t. We do not report estimates of the latter due to the fact that we lack regional grid quality data and our expectation of significant omitted variable bias related to electricity tariff increases. We do, however, control for the national-level SAIDI, S_t, interacted with former generator reliance. We thus estimate the differential effect of fuel tariff changes across firms with and without generator ownership (in the past), relying on the following reduced-form regression equation:

$$\begin{aligned} y_{isdt} = & \beta_0 + \beta_1 G_{isd0} \times D_t + \beta_2 G_{isd0} \times E_t + \beta_3 G_{isd0} \times S_t \\ & + \gamma X_{isdt-2} + \lambda_i + \kappa_{dt} + \gamma_{st} + \epsilon_{isdt}, \end{aligned} \tag{3.1}$$

where y_{isdt} denotes a set of dependent variables including generator use, generator capacity, energy intensity (mega joule per value added), emission intensity (kgCO$_2$e per value added), total sales, value added, value added per worker (as a measure of labour productivity), estimated revenue-based total factor productivity (TFPR), number of workers, material inputs and capital stock. All monetary values are deflated by the respective national price index and either *log*-transformed or, where necessary due to zero-valued observations, *asinh*-transformed. TFPR is estimated using the method proposed by Ackerberg et al. (2015) (see Appendix C for details). All standard errors are clustered at the firm level.

The vector of controls X_{isdt-2} includes controls for input use, including the number of workers, capital stock, and the value of material inputs, all lagged by two years in order to reduce the scope of a direct feedback from fuel and electricity prices to input use.[6] We exclude the lagged number of workers when estimating labor outcomes, lagged capital in the regression estimating capital stock adjustments, while material inputs are only included for estimating total sales. All regressions are conditional on firm fixed effects λ_i that capture all time invariant sources of heterogeneity. District-year fixed effects κ_{dt} control for a wide variety of location-specific shock, including most importantly improvements in the electricity grid, but also all other place-based

[6]The model is estimated using a panel of manufacturing establishments over 18 years (1998 to 2015), which allows us to cover the period from 2000 to 2015, for which tariff data are available.

policies that affect firm outcomes. The five-digit-sector-year effects γ_{st} flexibly control for a wide range of factors that affect all firms that produce very similar products, and should capture dynamics of sector-specific electricity sensitivity as defined by Alby et al. (2012).

While we control for observable determinants of generator ownership in the above regression (sector and district effects, as well as firm size measured by capital stock and number of workers), generator ownership will be correlated with firm size. Hence, estimates are likely to be biased. To tackle this, we use entropy balancing (for details, see Hainmueller, 2012) to construct weights for our control observations based on firm size in order to ensure that we compare similar firms to each other (for similar procedures, see e.g., Imbruno and Ketterer, 2018; Arnold et al., 2011; De Loecker, 2007). We include firm size measures (labor and capital) and a measure of sector-specific electricity sensitivity (defined as average kWh per value added). The weights are estimated for each survey year separately. With this procedure, we achieve balance in capital stock and labor force size (standardized differences in means below 0.01, see Table A3.2 in the appendix).

The matching procedure relies on the assumption of a selection on observables (conditional independence assumption, see e.g., Rosenbaum and Rubin, 1983). We compare firms that use a generator with firms that, given objective criteria, have a similar likelihood of being generator users. The decision of the latter type of firms to not rely on a generator could be related to differences in management styles that are not observed, or location-specific restrictions such as insufficient space to accommodate generators. To the extent that these styles or location-specific characteristics are correlated with reactions to price increases, our estimates will be biased. However, it is unlikely that such styles would dominate reactions to energy price increases, as the cost structure likely drives adjustment at the establishment level. Another concern with respect to identification is related to the estimation of both gross output and value added production functions. In the reduced-form regressions, we do not control for productivity shocks that are observed by the firm, but not by us. Thus, estimates of output elasticities with respect to each input (capital, labor and intermediate inputs) are likely biased (Gandhi et al., 2020; Ackerberg et al., 2015). This, however, is not a major concern, since the exact estimation of these elasticities is not our central goal. The price shocks caused by tariff adjustments are plausibly exogenous, and thus the differential effect of these price increases on generator users versus non-users should not depend on current levels of inputs or unobserved idiosyncratic productivity shocks of firms.

3.4 Results

Impact on generator use and energy and emission intensities We now turn to impact estimates (Equation 3.1). We begin by examining the relative effects (of generator-reliant versus

Table 3.2: Results for generator use and capacity, as well as energy and emission intensities

	Generator ...		Intensities	
	... use	... capacity (*asinh* kW)	Energy	Emissions
	(1)	(2)	(3)	(4)
Past generator owner	-0.295***	-1.527***	-0.021	-0.028
× *log* diesel tariff	(0.012)	(0.073)	(0.033)	(0.033)
Observations	111,828	106,278	111,828	111,828
Adjusted R-squared	0.637	0.671	0.588	0.589
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes	Yes
5-digit-sector-year FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

other firms) of energy price increases on the probability of using a generator (column 1 in Table 3.2). Diesel price increases have a strong negative impact: a 10 percent tariff increase is associated with a roughly 3 percentage point decrease. Average capacity installed decreases strongly when diesel tariffs increase (column 2): a 10 percent increase leads to a 15 percent reduction. Both effects are quite large and indicate that the price of diesel fuel significantly influences the decision of firms to maintain generator operation. Since (some) firms dis-adopt generators when diesel tariffs rise, we also expect to observe a comparative decline in energy and emission intensity because the use of generators is associated with higher energy and emission intensities (see Appendix B). Results are reported in columns 3 and 4 of Table 3.2. Contrary to our expectations, we find no statistically significant effects on neither energy nor emission intensity. However, both point estimates are negative. The true impact on average intensities may be small, so that we lack statistical power to detect it even though we know that energy and emission intensities should “mechanically” drop on average.

Impact on firm performance Estimation results of our impact analysis regression specification for firm performance indicators are shown in Table 3.3. A diesel tariff increase of 10 percent causes a relative decline in total sales of about 0.9 percent, on average. Results for the impact on value added point in the same direction: An increase of 10 percent is associated with a decline in value added by about 0.9 percent. We find no effects on both measures of productivity (columns 3 and 4). These results indicate that the short term impacts of diesel price increases on firm performance are different for firms using a generator than for firm not using a generator (in the past). Diesel price increases primarily cause a (relative) reduction in total

Table 3.3: Results for performance indicators

	log Sales	*log* VA	*log* VA/worker	*log* TFPR
	(1)	(2)	(3)	(4)
Past generator owner	-0.093***	-0.086***	-0.029	-0.004
× *log* diesel tariff	(0.023)	(0.025)	(0.022)	(0.004)
Observations	111,037	111,828	111,828	109,302
Adjusted R-squared	0.884	0.858	0.668	0.871
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes	Yes
5-digit-sector-year FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

sales as well as value added.

Adjustments of input demand We have established that firms that have used generators in the past decrease production and value added compared to firms without past generator use when diesel prices rise. However, we do not find impacts on productivity measures. This indicates that firms adjust factors of production in order to avoid productivity losses. Indeed, we find that firms with past generator use adjust their labor input when diesel prices rise: These firms decrease the labor force by about 0.7 percent for a ten percent diesel tariff increase compared to other firms (Table 3.4). Likewise, the value of material inputs of firms with past generator use decreases by 0.8 percent for a 10 percent tariff increase. Generator-reliant firms exhibit no differential impact on the capital stock compared to other firms. Since we investigate the short term effects of rising energy prices during the same year, it is not surprising that we do not find statistically significant impacts on the capital stock; capital accumulation (or diminishment) typically takes longer than one year. We will revisit the impact of rising diesel tariffs on capital stock in the robustness Section.

3.5 Robustness

In this robustness Section, we first look at “pre-event” graphs of the diesel subsidy reform. The interaction between the generator reliance measure and diesel tariff prices in equation 3.1 is replaced by a sum of interactions between the generator reliance measure and year dummies. Results on performance measures and input use of firms should turn statistically significant only during or after 2005, the year of the subsidy reform. In case firms with prior generator use have been on a divergent trend compared to firms without prior generator use, our impact estimates

Table 3.4: Results for inputs: Capital, labor, and materials

	log No. of workers	*log* Capital	*log* Materials
	(1)	(2)	(3)
Past generator owner	-0.073***	-0.016	-0.083***
× *log* diesel tariff	(0.015)	(0.029)	(0.029)
Observations	111,828	128,554	111,828
Adjusted R-squared	0.913	0.826	0.848
Firm controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes
5-digit-sector-year FE	Yes	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

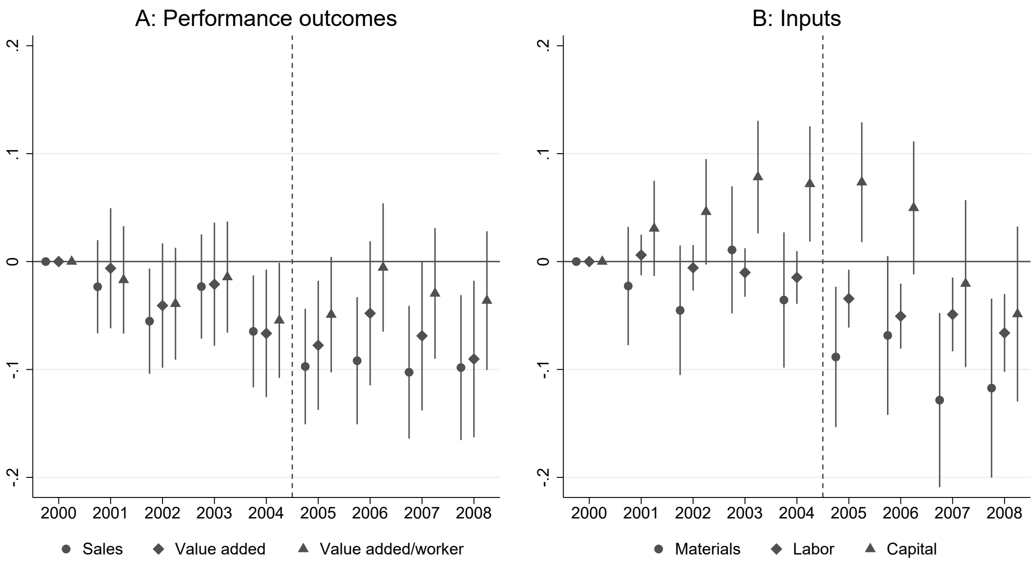
may reflect a trend of decreased performance rather than a causal effect of the reform.[7]

Estimates of the interactions between the generator reliance measure and the year dummies are presented in Figure 3.4. In Panel A, results from three different regressions on performance indicators are shown. Prior to 2005, we observe that all three estimates turn negative. In year 2003 and 2001, none of the estimates are statistically significant. During and after 2005, we observe a sustained negative impact on firms with past generator use on total sales and on value added (the latter significant at the ten percent level in 2006). Hence, some of our results on total sales may reflect causes other than differential effects of diesel price increases, such as changes in grid quality, for which we can unfortunately not control. However, this pre-trend analysis does not indicate that our main results regarding performance measures are entirely invalid.

Panel B shows the results from three different regressions on input use. Both labor and material input impacts turn negative and statistically significant during and after 2005. Hence, impact estimates on material input use likely do not pick up a differential trend between firms with and without past generator use. The case of differential capital stock movements requires a closer look. Before 2005, firms with generator use started accumulating capital to a larger extent compared to firms without prior generator use. After the subsidy reform in 2005, this trend slowly reversed. Hence, we find weak evidence for a (lagged) trend reversal.

In another robustness check, we investigate whether our results are sensitive to a particular weighting scheme. We present results of a regression with weights computed with the covariate balancing propensity score method (for details, see Imai and Ratkovic, 2014) in Appendix E. Results are similar compared to our main results.

[7]Results of the regression estimating the differential impact of diesel tariffs during 2000–2008 are presented in Appendix D. Results are comparable to our main results.



Notes: Vertical line marks the year before the major diesel fuel tariff reform.

Figure 3.4: "Pre-event" graph

3.6 Conclusion

This paper investigates the effects of fuel price increases on manufacturing firms in Indonesia. Correlations between grid electricity supply quality, tariff movements and generator use and capacity suggest that both grid quality and price dynamics greatly influence a firms' decision to invest in a generator. With rising fuel prices, firms dis-adopt generators, while electricity price increases are associated with investments into a generator, both by firms that have not been using generators before as well as firms with prior generator use.

Exploiting exogenous variation in tariffs for a rich data set by employing matching techniques in combination with panel regression analysis, we show that firms reliant on generators to self-produce electricity respond more strongly to fuel price increases than firms not reliant on generators. Our impact estimates show that diesel tariff increases lead to decreases of generator reliant firms' output as well as their value added by around 0.9 percent each for a 10 percent diesel tariff increase. Likewise, material input demand decreases by about 0.8 percent. Labor demand is adjusted flexibly and falls by around 0.7 percent, preventing productivity losses. We further show that diesel tariffs discourage generator use: a 10 percent tariff increase is associated with a 3 percentage point decrease in the incidence of generator use. Moreover, average installed generator capacity falls strongly by around 15 percent for a 10 percent increase in diesel tariffs. We hypothesize that both the reduction of generator use (at both the intensive and extensive margins) as well as higher costs for self-generated electricity causes the reduction in total output, value added, and material inputs, as well as subsequent reduction in labor demand to prevent productivity losses.

These findings have implications for countries considering fossil fuel subsidy reforms, carbon pricing or face sharply rising fossil fuel or electricity prices for other reasons. We show that fossil fuel price increases can have important effects on the performance of manufacturing sector when it is relying on generator use to a large extent, as firms that use generators reduce production relative to firms that do not use generators. Countries that prioritize low carbon economic development would be ill-advised to push firms into using generators: Increasing electricity tariffs without investment into the expansion and reliability of the electricity grid is not advisable if emission abatement is a priority, since generator use is associated with higher energy and emissions intensity of production. Hence, investment in the electricity grid should be prioritized (ideally powered by fuels with low emission intensity, or renewable energy) before considering ambitious carbon pricing to prevent competitiveness losses in the manufacturing sector.

Chapter 4

Household welfare and CO_2 emission impacts of energy and carbon taxes in Mexico

4.1 Introduction

Mexico has become a major emitter of greenhouse gas emissions in recent decades, with both economic and population growth as driving forces. In response, the Mexican government committed to carbon dioxide emission reductions relative to a baseline scenario and passed a climate change law in 2012 with legally binding emission-reduction goals (Vance, 2012). Additionally, substantial reform efforts have been made in the energy sector since 2013, which may affect energy prices. The oil and gas industry has been opened to competition in the up-, middle-, and downstream sectors, and Mexican households will be subjected to international gasoline prices by 2018. The Federal Electricity Commission (CFE) has been reformed with the objective of forming and regulating a competitive electricity market with incentives for private investment (IEA, 2017). In the residential electricity market, large seasonal subsidies continue to exist in warmer regions of Mexico to cover higher demand for air conditioning (IEA, 2016a; Davis et al., 2014; Komives et al., 2009).

While the effects of these reforms on energy consumer prices may be uncertain in some cases (oil sector) or modest in others (gasoline price subsidies), energy subsidy cuts and an

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ambitious climate policy are likely to increase energy prices in a country with a fossil-fuel reliant energy system. Higher energy prices are thus likely to lead in the short-run to welfare losses that may not be equally distributed. In developed countries, poorer households tend to be more vulnerable to energy price increases, as energy goods usually represent a larger proportion of their total expenditure, with some exceptions for transport fuels (Speck, 1999; Flues and Thomas, 2015). For developing countries, although there is less evidence on the distributional effects, Shah and Whalley (1991) as well as Shah and Larsen (1992) pointed out early on that the emerging distributional patterns are apparently different. Recent results in Sterner (2011) and Granado et al. (2012) show that high-income households capture significantly higher amounts of subsidies for fuels than low-income households. A similar result is found by Datta (2010), who investigates the distributional welfare effects of a fuel tax in India. Gillingham et al. (2006) show that the direct (consumption losses via higher prices) and indirect (income effects) welfare impacts of fuel price increases (both domestic and transport fuels) are either regressive or distributionally neutral in relative terms for a range of developing countries.

For Mexico, recent evidence on the distributional effects of subsidy removal and carbon taxes is provided by Rosas-Flores et al. (2017) who find that a reduction of gasoline subsidies is progressive. In a theoretical general equilibrium model for Mexico, Gonzalez (2012) shows how the distributional effect strongly depend on revenue recycling. While not explicitly covering distributional effects, Rivera et al. (2016) find a possible double dividend for climate policy in Mexico.

Most of the growing partial equilibrium literature on the welfare effects of energy price changes or subsidy reforms focuses on single fuels, with a strong emphasis on gasoline. As households usually spend income on more than just one fuel, an understanding of substitution patterns between fuels and other goods is essential to understanding the welfare effects of energy price changes. With the exception of Rosas-Flores et al. (2017), there is limited evidence for Mexico, where a clear understanding of household responses and welfare effects is particularly critical. In Mexico, nearly half of the population still lives below the official poverty line (Consejo Nacional de Evaluacion de la Politica de Desarrollo Social (CONEVAL, 2014)). Potentially large welfare losses due to higher energy prices are particularly critical in a country with relatively high CO_2 emissions; ambitious climate policy targets; and the need for further economic development, growth, and poverty reduction.

Against this background, the present study adds to the literature in two ways. First, we provide some evidence on the short-run poverty and distributional effects of energy price changes for Mexico. We calculate the welfare impacts of hypothetical price increases for electricity, motor fuels, gas, and public transportation. Since these price changes can be interpreted as environmental taxes, we can also assess how tax revenues can be redistributed for example, by employing cash transfers to households. In addition to assessing price changes for energy items, we simulate the welfare impacts of scaling up the carbon tax that was initially introduced in 2014. By drawing on the demand estimates, we examine whether second-order effects need to be calculated for the welfare analysis in our context. By estimating a censored consumer-demand system, we incorporate the discrete choice to use certain energy types and the exact pattern of substitution between them and other goods. Second, we calculate the short-run CO_2-emission-savings potential of consumer responses due to energy and carbon taxes. CO_2 emissions are calculated from a demand-side perspective on the basis of household consumption, also known as carbon footprints.

The rest of the paper proceeds as follows. First, we present the database on which the analysis is based, with some descriptive statistics, in Section 4.2. In Section 4.3 we describe the theory and the closely connected empirical strategy for measuring welfare effects and household-induced CO_2 emissions. We present the results in Section 4.4, before concluding in Section 4.5 with some policy recommendations.

4.2 Household Energy Use

We use household expenditure data from Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) surveys conducted by the Instituto Nacional De Estadistica y Geografia (INEGI), the national institute for geography and statistics in Mexico. The data are representative at both the national level and for rural and urban areas. They contain itemised expenditure information for every household, as well as an extensive list of variables capturing household and sociodemographic characteristics. The expenditure categories used in the analysis are (1) electricity, (2) motor fuels (including low-/ and high-octane gasoline as well as diesel and gas), (3) gas (aggregate of natural gas and liquefied petroleum gas [LPG]), (4) public transportation, (5) food (excluding alcohol and tobacco), and (6) other goods. Figure 4.1 shows the distribution of energy expenditures over expenditure percentiles for 2014.[1] Expenditures for the four energy goods relative to total expenditures range between 6 and 13 percent of total household expenditures. A clear reverse U-shaped curve can be observed for total energy budget shares over the total expenditure distribution.

Figure 4.2 plots the distributional incidence for the energy goods separately and also distinguishes between users and non-users. This distinction matters for welfare analyses, as users of certain energy goods may not find it so easy to switch away from using them. Households may own vehicles and other energy-processing durables that they do not want to (or cannot) put out of use. When all observations are considered, the electricity consumption share decreases continuously over the expenditure distribution, but it exhibits little variation across percentiles and lies at approximately 2.4 percent for the poorest households. The slightly declining budget

[1]Nonparametric distributional curves are calculated with kernel-weighted local polynomial smoothing using an Epanechnikov kernel function with degree 0 and bandwidth 1.15.

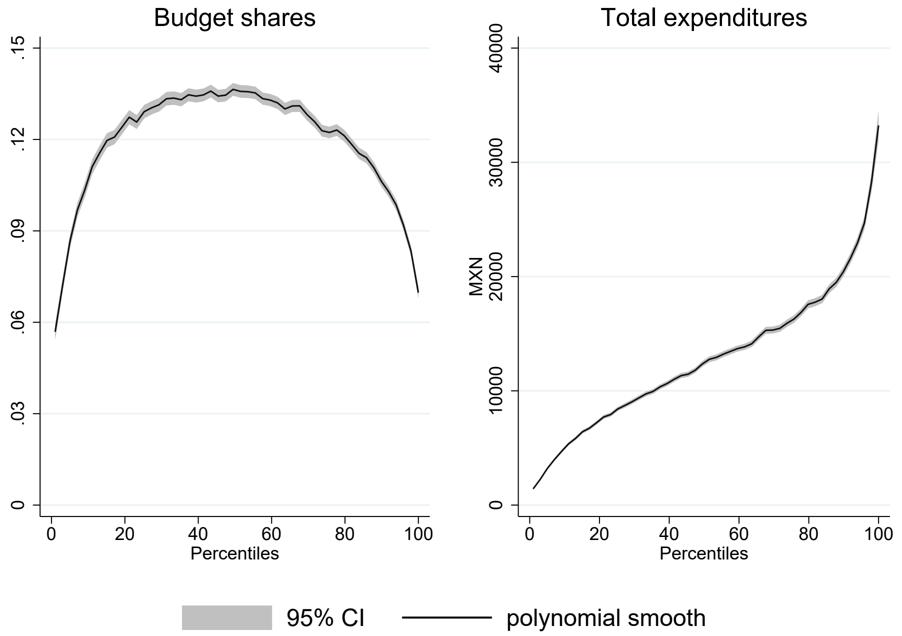

Figure 4.1: Energy Expenditures

shares over the income distribution pattern are not found universally in other countries. For example, in Sri Lanka, Mali, and Indonesia, richer households exhibit larger electricity budget shares (Gillingham et al., 2006), partly as a result of the design of electricity tariffs. For motor fuels, the share increases over the expenditure distribution, ranging from approximately 1.6 percent to 4.3 percent. Both gas and public transport exhibit an inverse U-shaped curve over the expenditure distribution, with gas being the least important energy good.

When only those households with positive expenditures for the respective energy goods are considered, budget shares decrease continuously with income for all energy types. The difference between users and non-users is most pronounced for motor fuel expenditures for the first decile, for which the mean share is just above 10 percent. Note that only around 16 percent of the households in the poorest decile own a vehicle, compared to 73 percent in the richest decile. Poor households that use gas also have a larger expenditure share than rich ones. Public transport expenditure shares for users reach nearly 10 percent for the first decile and decline over the expenditure distribution. Only minor differences in electricity expenditure shares are detected due to a high electrification rate. These findings indicate that the distributional incidence of relative expenditures depends heavily on the usage rate in the respective income groups. Poor households that depend on one of these energy goods might be disproportionately vulnerable when subjected to energy price increases. The data indicate that motor fuel usage in the poorest decile, that is, the percentage of households consuming some motor fuel increased from 4.5 percent in 2002 to 1 percent in 2014. Poor households have thus become more vulnerable to motor-fuel price increases. We find that rural households spend slightly less of their current

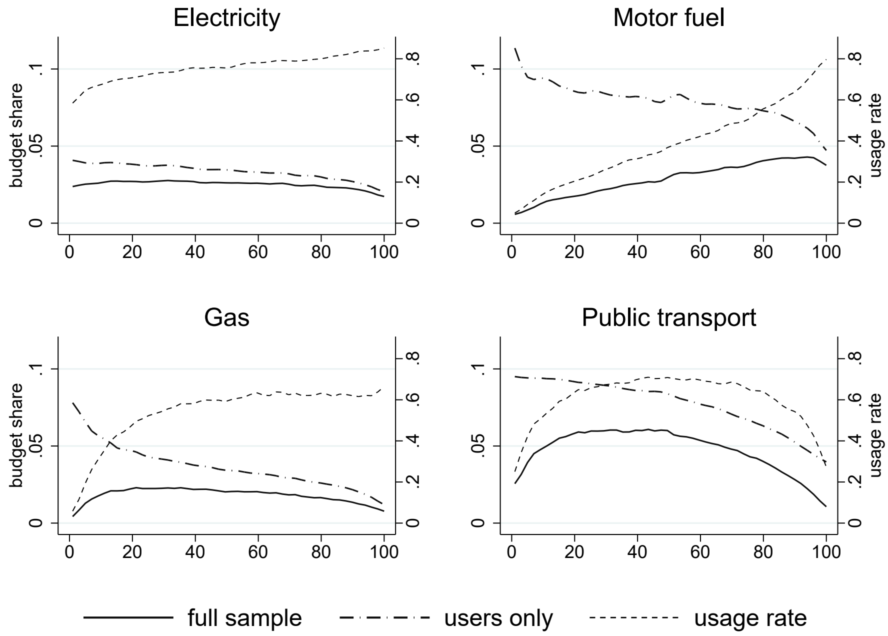

Figure 4.2: Energy Budget Shares and Usage Rates

income on electricity than urban households. For the other energy goods, the data shows no significant difference in consumption patterns between rural and urban households.[2]

4.3 Methodology

4.3.1 Demand System

We model the demand for electricity, motor fuels, gas, public transport, food, and other non-durables based on household survey data with a microeconomic, partial equilibrium demand framework. For our analysis we use the Quadratic Almost Ideal Demand System (QUAIDS) framework (Banks et al., 1997), since observed Engel curves appear to be well approximated by a quadratic relationship between budget shares and logarithmic transformed expenditures.[3] The estimation of a QUAIDS has been applied to the energy context by Brännlund and Nordström (2004) for Sweden, Labandeira et al. (2006) for Spain, Nikodinoska and Schröder (2016) for Germany, and Tiezzi and Verde (2016) for the United States, but according to our knowledge, no demand system specification of this type has been applied to the energy context in low- and middle-income countries to date.

As a rank three quadratic logarithmic budget share system, the QUAIDS has an indirect

[2]Results not reported.

[3]For higher observed non-linearity, other systems such as the EASI from Lewbel and Pendakur (2009) would be more appropriate.

utility function that takes the following form:

$$\ln V = \left\{ \left[\frac{\ln x - \ln a(p)}{b(p)} \right]^{-1} + \lambda(p) \right\}^{-1} \tag{4.1}$$

The price indexes $\ln a(p)$ and $b(p)$ are defined as:

$$\ln a(p) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln p_i \ln p_j \tag{4.2}$$

$$b(p) = \prod_{i=1}^{n} p_i^{\beta_i} \tag{4.3}$$

The term $\lambda(p)$ in the indirect utility function is a differentiable, homogeneous function of degree zero of prices p and defined as:

$$\lambda(p) = \sum_{i=1}^{n} \lambda_i \ln p_i \tag{4.4}$$

with $\sum_i \lambda_i = 0$ the derived expenditure share system is:

$$w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln \left[\frac{x}{a(p)} \right] + \frac{\lambda_i}{b(p)} \left\{ \ln \left[\frac{x}{a(p)} \right] \right\}^2 \tag{4.5}$$

where w_i is the share of commodity (group) i of total expenditures x. To be consistent with utility maximization, the following restrictions need to hold:

Adding-up

$$\sum_{i=1}^{n} \alpha_i = 1; \quad \sum_{i=1}^{n} \gamma_{ij} = 0; \quad \sum_{i=1}^{n} \beta_i = 0; \quad \sum_{i=1}^{n} \lambda_i = 0 \tag{4.6}$$

Homogeneity

$$\sum_{j=1}^{n} \gamma_{ij} = 0 \tag{4.7}$$

Symmetry

$$\gamma_{ij} = \gamma_{ji} \tag{4.8}$$

Budget elasticities can be derived from the share equation:

$$e_i = \frac{\mu_i}{w_i} + 1 \tag{4.9}$$

with

$$\mu_i = \frac{\partial w_i}{\partial \ln x} = \beta_i + \frac{2\lambda_i}{b(p)} \left\{ \ln \left[\frac{x}{a(p)} \right] \right\} \tag{4.10}$$

The uncompensated price elasticity is given by:

$$e_{ij}^u = \frac{\mu_{ij}}{w_i} - \delta_{ij} \tag{4.11}$$

with

$$\mu_{ij} = \frac{\partial w_i}{\partial \ln p_i} = \gamma_{ij} - \mu_i \left(\alpha_j + \sum_k^n \gamma_{jk} \ln p_k \right) - \frac{\lambda_i \beta_j}{b(p)} \left\{ \ln \left[\frac{x}{a(p)} \right] \right\}^2 \tag{4.12}$$

and δ_{ij} is the Kronecker delta. Compensated price elasticities are derived by the slutsky equation

$$e_{ij}^c = e_{ij}^u + e_i w_j \tag{4.13}$$

Demographic demand shifters including sex, age, education of the household head, household size and a rural area dummy influence preferences through α_i in equation 4.5. To account for zero expenditures, we follow Shonkwiler and Yen (1999) and obtain elasticity estimates in a censored system setting. In first step, a household specific probit model is estimated with the outcome of 1 if the household consumes good i and 0 otherwise. For each household in the sample, the standard normal probability density function (pdf) $\varphi(z_{ih}, w_i)$ and the cumulative distribution function (cdf) $\Phi(z_{ih}, w_i)$ are calculated by regressing w_i on a set of independent variables z_{ih}. In a second step, the pdf and the cdf are integrated into the system of equations:

$$w_i^* = \Phi w_i + \varphi_i \phi \tag{4.14}$$

Opposed to Heckman (1979), this approach is based on the full sample in both steps of the estimation process. The elasticities change as:

Expenditure elasticity

$$e_i^* = \frac{\Phi(\mu_i)}{w_i} + 1 \tag{4.15}$$

Price elasticity

$$e_{ij}^* = \frac{\Phi(\mu_i)}{w_i} + \phi \tau_{ij} (1 - \frac{\varphi_i}{w_i}) - \delta_{ij} \tag{4.16}$$

Since we use prices as dependent variables in the first stage estimation, τ_{ij} is the coefficient of price j from equation i from the probit model. The respective expenditure and price elasticities, e_i and e_{ij} are derived under the modified system (4.14). Explanatory variables used in the probit estimation are listed in table 4.2. This two-step methodology has been extensively applied in agricultural demand contexts (see for example Ecker and Qaim (2011); Shonkwiler and Yen (1999); Yen et al. (2002)) but not yet for energy demand. The censored system is estimated for the full system and therefore loses the adding-up restriction, which is why we calculate approximate second-order welfare effects based on equation (20). We use a two-step feasible generalized nonlinear least squares (FGNLS) estimator for the estimation of equation (17). Identification of price elasticities is enabled through cross-sectional (spatial) and time variation. We select eight years for the demand system estimation: 2002, 2004, 2005, 2006, 2008, 2010, 2012 and 2014. Additional to this considerable variation in time, spatial variation comes from CPI data on the city level. The price data consist of indices that are available from INEGI for 46 cities throughout Mexico and every state is represented by at least one city. Households not residing in one of the 46 cities are assigned to the city that is located in their state. When more than one city lies in the respective state, an unweighted average of the price indices is calculated. The price indices are disaggregated for the categories food, gasoline, electricity, gas (aggregated index for both LPG and natural gas) and public transport (inter alia). For other goods, we use the general price index. For motor fuels, we use the aggregated index of low- and high-octane gasoline. To correct for city specific effects, we incorporate city fixed effects in the α_i term in equation 4.5.

4.3.2 Simulation and welfare effects

We simulate price changes for different scenarios, where the price change per good i is simply:

$$\frac{\Delta p_i}{p_i^0} = \frac{p_i^1 - p_i^0}{p_i^0} \tag{4.17}$$

and the new price level after the tax change is:

$$p_i^1 = \left(1 + \frac{\Delta p_i}{p_i^0}\right) p_i^0 \tag{4.18}$$

$\ln a(p)$ and $b(p)$ (equation 4.14) get adjusted accordingly with new price levels and we obtain simulated budget shares for good i and each household according to:

$$\begin{aligned} w_i^1 = \Phi\Bigg(&\widehat{\alpha_i} + \sum_{j=1}^{n} \widehat{\gamma_{ij}} \ln p_j^1 + \widehat{\beta_i} \ln\left[\frac{x^0}{a(p^1)}\right] + \frac{\widehat{\lambda_i}}{b(p^1)} \left\{\ln\left[\frac{x^0}{a(p^1)}\right]\right\}^2\Bigg) \\ &+ \varphi_i \phi + \widehat{\epsilon_i}^0 \end{aligned} \tag{4.19}$$

The *hats* are estimated coefficients from equation 4.14 and the superscripts denote the periods of reference. Household characteristics in the α term remain unchanged in all scenarios. Since the demand system does not predict household expenditures perfectly, the residual term ϵ_i containing household specific unexplained effects is included.[4]

[4]Additionally, with the missing adding up restriction, budget shares do not add up perfectly to 1. We find this error to be very small in our simulations, in the range of 0.03–0.3 percentage point deviation.

The literature on the welfare impacts of energy price increases and subsidy reforms focuses to a large extent on first-order effects as in Sterner (2011). These first-order effects, based on work of Feldstein (1972) and Stern (1987) only require the observed demand and no additional information on substitution behavior due to price changes. First order welfare losses relative to income (total expenditures are used as a proxy) are calculated as:

$$FO = \sum_{i=1}^{n} w_i \left(\frac{\Delta p_i}{p_i^0} \right) \tag{4.20}$$

With estimated coefficients at hand, we calculate a second-order approximation to the Compensating Variation (CV), which is the amount of money the household needs to be compensated with to attain the utility level u^0 prior to the price changes, again relative to total household expenditures:[5]

$$CV = \sum_{i=1}^{n} w_i \left(\frac{\Delta p_i}{p_i^0} \right) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} w_i e_{ij} \left(\frac{\Delta p_i}{p_i^0} \right) \left(\frac{\Delta p_j}{p_j^0} \right) \tag{4.21}$$

The CV is compared to the first-order effect to clarify the necessity of estimating a demand system in our context. The price change in equation (4.17) can also be interpreted as an ad valorem tax rate t_i. Tax payments per household are then calculated as:

$$T = \sum_{i=1}^{n} \frac{\Delta p_i}{p_i^0} (p_i^0 * q_i^1) = \sum_{i=1}^{n} t_i \frac{exp_i^1}{1 + \frac{\Delta p_i}{p_i^0}} \tag{4.22}$$

which are multiplied with household weights and summed over all households to obtain the total tax revenue. With household substitution already incorporated, simulated expenditures based on equation 4.19 are used for the tax calculation and deflated to the base period. When tax revenues are redistributed to households in the form of direct cash transfers, we assume the additional income is completely spent on non-durable consumption and the new budget shares are:

$$\begin{aligned} w_i^{1,tr} = \Phi \Bigg(& \widehat{\alpha_i} + \sum_{j=1}^{n} \widehat{\gamma_{ij}} \ln p_j^1 + \widehat{\beta_i} \ln \left[\frac{x^1}{a(p^1)} \right] + \frac{\widehat{\lambda_i}}{b(p^1)} \left\{ \ln \left[\frac{x^1}{a(p^1)} \right] \right\}^2 \Bigg) \\ & + \varphi_i \phi + \widehat{\epsilon_i}^0 \end{aligned} \tag{4.23}$$

4.3.3 CO_2 emissions

In our analytical framework, CO_2 emissions (C) are calculated from a demand side perspective. The carbon content of the goods in our analysis may come from three different sources.

[5] The approximation is based on a second-order Taylor series expansion of the expenditure function (Banks et al., 1996; Deaton and Muellbauer, 1980; Friedman and Levinsohn, 2002)

First, fuels have a direct CO_2 content per physical unit (C_{dir}).[6] Second, goods are produced with energy which leads to the emission of CO_2, the direct production emissions. Third, other goods used in the production process are responsible for the indirect production emissions. We term production emissions from direct and indirect energy use as indirect emissions C_{ind}. Total emissions C are simply the sum of direct and indirect emissions:

$$C = C_{dir} + C_{ind} \tag{4.24}$$

Where applicable, as in the case of fuels, C_{dir} can be calculated based on the expenditure data. The indirect emissions C_{ind} are calculated with an environmentally extended input-output model based on data from the World Input-Output Database (Timmer et al., 2015) as:

$$C_{ind} = CI'x = CI'(I - A)^{-1}y \tag{4.25}$$

where CI is the direct carbon intensity of production, $(I - A)^{-1}$ the Leontief inverse and $CI'(I - A)^{-1}$ the indirect carbon intensities containing all direct and indirect production emissions.[7] These CO_2 emissions embedded in household consumption, the carbon footprints, are derived by multiplying expenditures per good with the respective carbon intensity CI_k (tCO_2/MXN):

$$CO_2^0 = \sum_{i=1}^{n}(exp_i^0 * CI_i) \tag{4.26}$$

In each scenario, new expenditure levels exp_i^1 per good i and each household are derived from new budget shares w_i^1. New carbon emissions are then calculated as:

$$CO_2^1 = \sum_{i=1}^{n}\left(\frac{exp_i^1}{1 + \frac{\Delta p_i}{p_i^0}} * CI_i\right) \tag{4.27}$$

For the calculation of tax revenue, the simulated expenditures are real expenditures at base prices. They isolate the unobserved quantity effect from the nominal expenditure change. Aggregating over households by using household weights, we obtain total carbon emissions resulting from domestic household demand. The difference to the baseline value is then exclusively explained by consumer substitution. Substitution effects are also taken into account in redistribution scenarios when total expenditures increase through cash transfers. New expenditure

[6]For motor fuels we assume the CO_2 content of gasoline: 2.31 kg CO_2/. Gas/LPG: 1.5 kg CO_2/kg. These physical units are transformed to CO_2 intensities per monetary unit by assuming prices of MXN 13 per l motor fuel and MXN 13 per kg of gas. Although this procedure is not precise due to different prices for households over space and fuel choice, it corrects for the otherwise missing direct carbon content on consumption in the absence of quantity information

[7]For details on the calculation of carbon intensities and matching with household expenditures for Mexico, see Renner (2017). The way in which we matched the 34 sector production classification to our 6-good demand classification is described in table A4.1

levels $exp_i^{1,tr}$ based on equation 4.23 are expected to be higher with normal goods and reduce the emission saving potential determined by the size of β and λ through the budget elasticity.

4.4 Poverty, welfare and CO_2 emissions

In order to understand the implications of energy price changes for household welfare and carbon footprints, we simulate separate stylised scenarios with price changes for each fuel, as well as one scenario with price changes for all energy types simultaneously. In a second step, we take a closer look at potential future policy interventions in the form of different carbon tax rates. In the process, we assess the importance of calculating second-order effects for welfare analysis in this context. For the effects on poverty, we calculate absolute welfare effects and subtract them from household income, since domestic poverty lines are constructed with household income per capita (CONEVAL 2014). We calculate Foster-Greer-Thorbecke (FGT) poverty indices on the basis of the poverty lines for Mexico provided by the National Council for the Evaluation of Social Development Policy CONEVAL (Consejo Nacional de Evaluacion de la Politica de Desarrollo Social). CONEVAL indicates two different poverty lines. One refers to extreme poverty, as illustrated by the minimum standard of individual well-being, which corresponds to the value of the food basket per person per month (Bienestar minimo - Canasta alimentaria). Those living below this poverty line cannot acquire enough food to ensure adequate nutrition. The second poverty line is equivalent to the total value of the food plus non-food basket per person per month and hence refers to a general standard of wellbeing (Bienestar - Canasta alimentaria y no alimentaria). We provide results for both poverty lines in order to distinguish between effects on extreme and moderate poverty.

4.4.1 Energy Price Changes

Since the direct interpretation of the coefficients is difficult, we report elasticities in Table 4.1. Following Banks et al. (1997), we calculate elasticities for each household individually and construct a weighted average, with the weights generated as the household's share of total sample expenditure for the relevant good. The estimated budget elasticities suggest that, on average, households perceive motor fuels as a luxury good and electricity, gas, and public transport as necessities. For the latter three energy items, income elasticities are fairly close to 1, which indicates quickly rising energy demand with income growth. Income plays a more nuanced role for the discrete energy use decision. Due to Mexico's very high electrification rate, income is not an important determinant of electricity use. In the case of motor fuel, income plays a major role in determining private transport vehicle ownership. The probability of public transport use, on the other hand, is only slightly affected by rising incomes, and more so by the necessity and convenience of this transportation mode, as reflected in the large effect of the rural dummy.

Uncompensated own-price elasticities all show the expected negative signs and reflect inelastic household responses to price changes with the exception of electricity and motor fuels. Cross-price elasticities between energy items show the expected pattern, for example, the domestically used electricity and gas and transport expenditures for motor fuel and public transport are substitutes, though fairly inelastic in nature. Compensated-price elasticities for energy items, used in the calculation of welfare effects, do not differ significantly since expenditure elasticities are all close to 1. For food and other goods, the elasticities become indistinguishable from 0. Based on the observance of energy price elasticities, we would not expect large differences between the first- and second-order welfare effects except in the case of electricity-price changes.

The descriptive analysis of budget shares has already revealed the potential distributional patterns of price changes for the respective energy types. Reflecting these expenditure patterns, the magnitude of a stylised price change of 20 percent per energy good is displayed in Figure 4.3. We find almost no difference between first- and second-order welfare losses. Overall, the calculated own-price elasticities imply, on average, a smaller second-order effect relative to the first-order effect. However, the use of 95 percent confidence intervals in the calculation of average welfare effects per percentile reveals no statistically significant difference with the exception of electricity. Electricity price changes have a slightly regressive effect as opposed to motor-fuel price changes, which are clearly progressive. Welfare losses for gas and public-transport price increases rise with expenditures until the 20th percentile and start falling from the 50th percentile. As expected from the descriptive analysis in Section 2, price changes for public transport have the potential to create the largest welfare losses for lowand middle-income households. Absolute welfare losses are strictly rising with expenditures for all energy goods. Simultaneous price increases for all energy-related expenditures lead to an inverse U-shaped distributional impacts curve (Figure 4.4). The magnitude of welfare losses is more distribution neutral and smaller in magnitude than welfare losses from food price increases, which are strongly regressive. With multiple price changes, the necessity of calculating second-order welfare effects is visible between the 20th and 90th percentiles. First-order effects overestimate the welfare loss by up to 10 percent for middle-income households.

As expected from the descriptive analysis of users versus non-users of energy types, the distributional results differ significantly for the average user with strictly positive demand for the respective energy good (Figure 4.5). While we see almost no difference for electricity, price increases for all other energy items are clearly regressive for the user part of the population. Taking motor fuel as an example, the population average progressive effects can be explained by the low car ownership rates of the lower part of the expenditure distribution. For public transport, a major share of rural low-income households appears to be less dependent on public transport. We therefore find smaller welfare losses than for the rest of the population. Although these differences between users and non-users shed light on heterogeneity in welfare effects within the same income group, the share of the population affected around the poverty lines is

Table 4.1: Demand Elasticities

Uncompensated Price Elasticities

		Price					
		Electr	M.Fuel	Gas	P.Trans	Food	Other
Demand	Electr	-1.49	-0.16	0.14	0.03	0.03	0.28
		(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
	M.fuel	-0.09	-1.03	0.02	0.10	0.26	-0.45
		(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
	Gas	0.18	0.04	-0.69	-0.16	-0.29	0.11
		(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)
	P.Trans	0.01	0.10	-0.06	-0.65	-0.74	0.63
		(0.000)	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)
	Food	0.01	0.06	-0.02	-0.15	-0.10	-0.50
		(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.001)
	Other	0.01	-0.03	0.00	0.05	-0.43	-0.73
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Compensated Price Elasticities

		Price					
		Electr	M.Fuel	Gas	P.Trans	Food	Other
Demand	Electr	-1.43	-0.12	0.16	0.06	0.30	0.82
		(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
	M.fuel	-0.06	-0.92	0.03	0.12	0.56	0.28
		(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
	Gas	0.20	0.07	-0.66	-0.13	-0.04	0.58
		(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)
	P.Trans	0.03	0.11	-0.05	-0.53	-0.44	1.00
		(0.000)	(0.001)	(0.001)	(0.002)	(0.004)	(0.003)
	Food	0.02	0.08	-0.01	-0.12	0.16	-0.24
		(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
	Other	0.04	0.01	0.02	0.09	-0.12	0.04
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Expenditure Elasticities

	0.96	1.22	0.84	0.85	0.60	1.20
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.000)

Standard errors in parentheses

Table 4.2: Probit Energy Demand (Marginal Effects)

	(1)	(2)	(3)	(4)
VARIABLES	electricity	motor fuels	gas	public transp
lnp1	-0.00634***	-0.134***	0.241***	0.160***
	(0.00127)	(0.00596)	(0.00664)	(0.00684)
lnp2	0.0485***	-0.369***	0.0204	0.415***
	(0.00614)	(0.0237)	(0.0269)	(0.0275)
lnp3	-0.0108***	0.150***	0.0558***	-0.106***
	(0.00226)	(0.0117)	(0.0133)	(0.0135)
lnp4	0.00653*	-0.322***	0.242***	0.332***
	(0.00347)	(0.0171)	(0.0193)	(0.0197)
lnp5	-0.0281***	0.794***	0.117**	-1.051***
	(0.0103)	(0.0508)	(0.0570)	(0.0582)
lnp6	-0.00596	-0.335***	-0.998***	0.418***
	(0.0151)	(0.0739)	(0.0825)	(0.0846)
ln(x)	0.00627***	0.317***	0.177***	0.0305***
	(0.000456)	(0.00178)	(0.00216)	(0.00224)
male	-0.00233***	0.156***	-0.000476	-0.0829***
	(0.000647)	(0.00286)	(0.00327)	(0.00336)
age	0.000299***	0.000955***	0.00189***	-0.00212***
	(1.94e-05)	(8.32e-05)	(9.24e-05)	(9.37e-05)
education	0.00103**	0.0758***	-0.0159***	-0.0707***
	(0.000482)	(0.00211)	(0.00246)	(0.00247)
household size	0.000599***	-0.00687***	0.00843***	0.0289***
	(0.000142)	(0.000654)	(0.000754)	(0.000770)
rural	-0.00331***	0.0754***	-0.136***	-0.143***
	(0.000553)	(0.00307)	(0.00336)	(0.00343)
Observations	117,656	117,656	117,656	117,656

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

more relevant for poverty incidence. Price increases for each energy type separately have quite modest impacts on the well-being poverty rate, with differences for each energy good (Figure 4.6). We calculate welfare losses for first- and second-order effects to assess the importance of taking into account substitution behaviour for poverty incidence. Price increases of up to 50 percent for the single energy items produce nearly identical poverty rate outcomes for first- and second-order effects. Only beyond this range do the differences become significant. For joint price increases for all energy goods, the difference between first and second-order effects

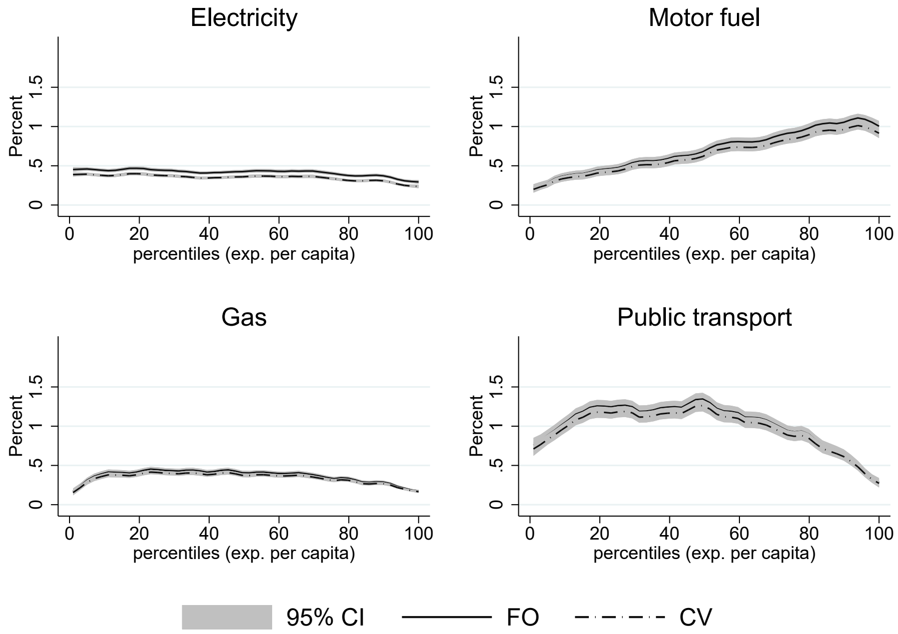

Figure 4.3: First- and Second-Order Welfare Effects (CV), Energy Items

starts earlier and is more pronounced. The domestically used electricity and gas both show little sensitivity to price increases with respect to the poverty rate. An electricity price rise of 50 percent would increase the well-being poverty rate by 0.5 percentage points maximum. Domestic energy prices for consumers in Mexico are relatively low in international comparison.

Energy price increases in general have less impact on poverty than food price increases, as reflected in a steeper gradient in Figure 4.6. Nevertheless, at the well-being poverty line, a 20 percent price increase for energy has substantial effects on poverty, with an increase in the poverty rate of 1.4 percentage points (Table 4.4). The higher budget shares and associated welfare effects for middle-income households, on average, also lead to greater increases in the well-being poverty rate for all energy goods and for food relative to the minimum well-being poverty rate (Table 4.3). In addition to experiencing changes in poverty, middle-income households close to the poverty line will be disproportionally affected by higher energy prices although they will not technically be defined as poor after the price change.

For each price increase, we calculate the resulting changes in the household carbon footprint (energy-related CO_2 emissions and CO_2-equivalent emissions including CH_4 and N_2O), as displayed in Table 4.5. Although motor fuel does not have the highest carbon intensity, a motor- fuel price increase/tax would create the largest emission reductions, driven by relatively large budget shares. Emission reductions through electricity price changes would also be large, determined by high price elasticities despite relatively small budget shares. Remarkably, taxing gas alone has no observable effect on CO_2 emissions. This seemingly counterintuitive result can be explained by positive cross-price elasticities with electricity. As a clear substitute and

Table 4.3: FGT Poverty Indices (in %), Changes from Baseline, Minimum Well-Being Poverty Line

	FGT	Electr.	Motor fuels	Gas	Publ. Transp.	Energy	Food
price change	0	0.143	0.099	0.169	0.373	0.785	3.077
	1	0.041	0.043	0.043	0.124	0.259	1.299
	2	0.019	0.022	0.019	0.057	0.122	0.692
+ lump-sum	0	-0.091	-0.481	-0.081	-0.215	-0.775	-1.307
	1	-0.030	-0.159	-0.046	-0.096	-0.323	-0.540
	2	-0.018	-0.084	-0.027	-0.058	-0.180	-0.293
+ PROSPERA	0	-0.213	-0.821	-0.308	-0.601	-1.820	-2.581
	1	-0.115	-0.377	-0.151	-0.330	-0.745	-0.622
	2	-0.067	-0.200	-0.088	-0.183	-0.357	-0.193

Table 4.4: FGT Poverty Indices (in %), Changes from Baseline, Well-Being Poverty Line

	FGT	Electr.	Motor fuels	Gas	Publ. Transp.	Energy	Food
price change	0	0.192	0.316	0.184	0.710	1.440	4.414
	1	0.097	0.127	0.123	0.356	0.720	2.687
	2	0.061	0.074	0.075	0.216	0.438	1.808
+ lump-sum	0	-0.015	-0.311	0.003	-0.043	-0.598	-0.925
	1	-0.043	-0.285	-0.056	-0.088	-0.475	-0.934
	2	-0.035	-0.205	-0.047	-0.086	-0.371	-0.688
+ PROSPERA	0	-0.046	-0.440	-0.117	-0.046	-0.647	-1.647
	1	-0.135	-0.531	-0.170	-0.352	-1.043	-1.571
	2	-0.118	-0.423	-0.151	-0.318	-0.816	-0.972

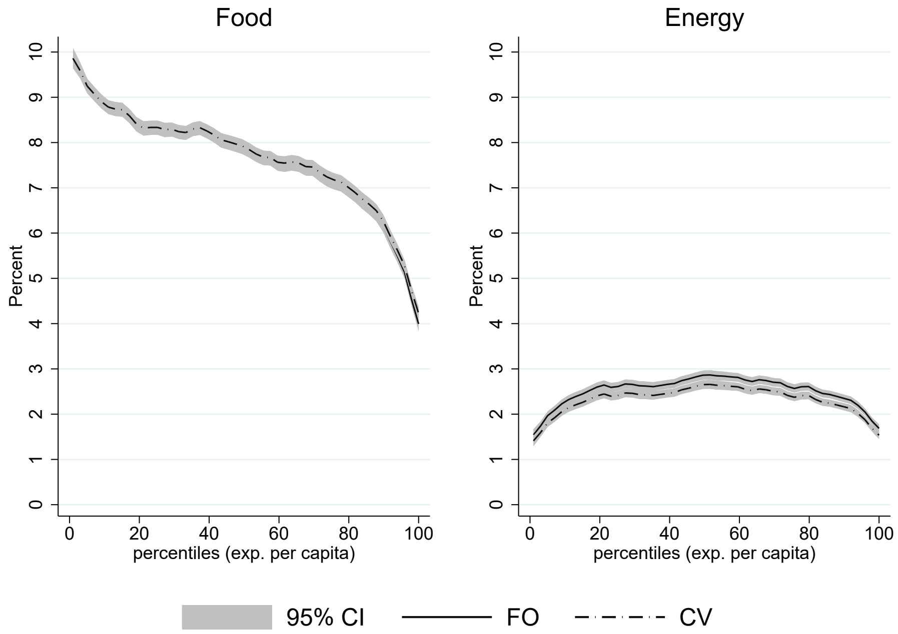

Figure 4.4: First- and Second-Order Welfare Effects (CV), Energy and Food

with higher carbon intensity, increased electricity demand turns the emission saving from reduced gas use into a small net emission increase. A similar finding can be observed for a tax on public transport, which results in zero emission savings due to substitution with motorised private transport. These findings demonstrate the importance of obtaining a full range of own- and cross-price effects to simulate integrated welfare-environmental models. Multiple price changes for all energy-related goods may lead to very strong emission reductions through decreased household demand. Food price increases have, as discussed above, significant effects on poverty, as well as a significant impact on energy-related CO_2 emissions. As households are estimated to have close to zero own-price elasticities for food, the complementary character of gas, public transport, and other goods accounts for the energyrelated emission reduction.

The redistribution of tax revenues leads to moderate progressive welfare effects when lump-sum transfers are used (Figure 4.7). For the most part, net taxes are paid by the rich households, with the exception of public transport, where the middle class pays the bill. If all tax revenues are redistributed solely to PROSPERA recipients, a governmental social assistance programme, progressivity becomes very strong, with large welfare gains of approximately 11 percent of expenditures for the poorest households in the case of motor fuel or public transport taxes.[8] Compared to the pure lump-sum scheme, households are less well compensated starting at the 50th percentile, which is also above the moderate poverty line. As a result, the poverty rate decreases by 0.65 percentage points at the well-being poverty line in the case of a simultaneous

[8] PROSPERA was formerly known as Oportunidades, which was rebranded in 2014.

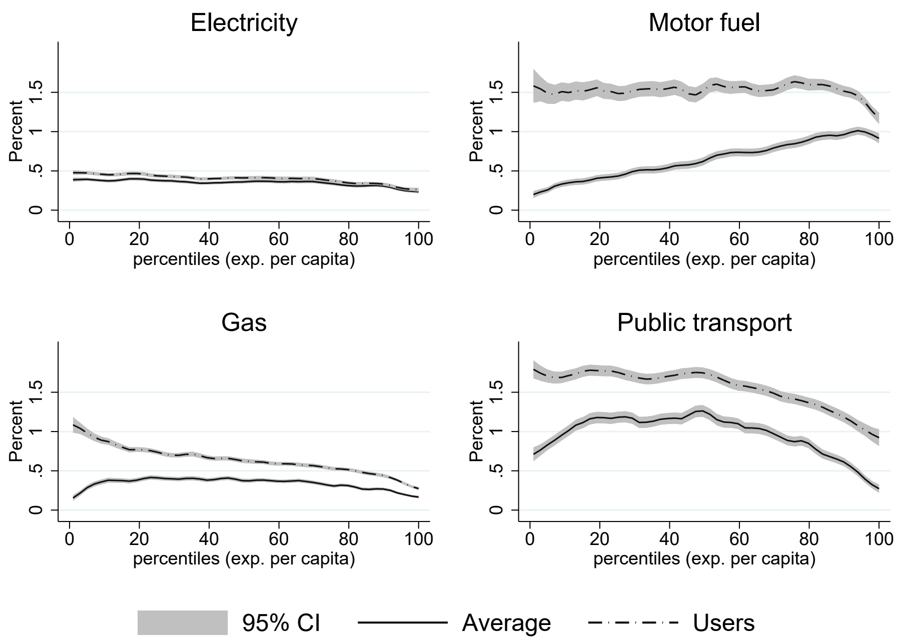

Figure 4.5: First- and Second-Order Welfare Effects (CV), Users vs. Average

tax of 20 percent on all four energy goods and redistribution via PROSPERA. On the other hand, poverty measured at the minimum well-being poverty line reacts more sensitively to redistribution through the relatively large compensation amounts. In this case and in the case of redistribution via PROSPERA, we find a reduction in the poverty rate of 1.8 percent. CO_2 reductions are slightly larger when redistribution takes place via PROSPERA rather than via universal lump-sum transfers, but the differences are small. When all energy-related goods are taxed at a rate of 20 percent and tax revenue is fully redistributed via PROSPERA, household CO_2 emissions are calculated to be 9.5 percent less than in the baseline and 1.5 percent less than without redistribution. On the other hand, a tax on food accompanied by the simultaneous redistribution of tax revenues has positive effects on household CO_2 emissions. Driven by increased demand for direct energy and other goods, the positive income effect from the relatively large redistribution amount has a strong effect on direct energy demand despite the negative cross-price effects on energy goods such as electricity.

4.4.2 Carbon Tax

The first-order welfare and poverty effects of a carbon tax in Mexico have been analysed in Renner (2017). We take their sector-specific price changes and apply them to our product categorisation to assess the validity of using first-order effects and to calculate the short-run CO_2 emissions-reduction potential when price increases are shifted completely to consumers.[9]

[9] Aggregation scheme available upon request.

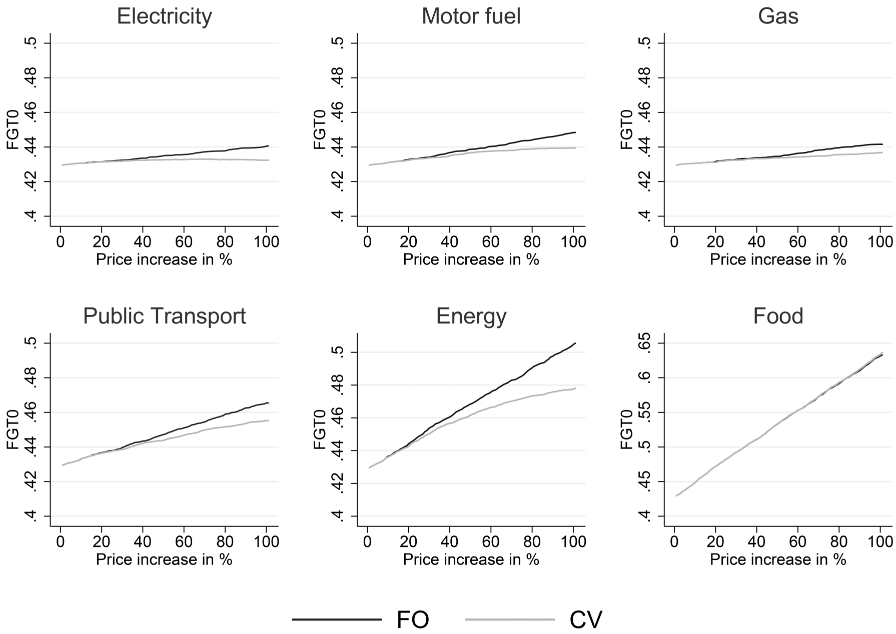

Figure 4.6: Poverty Rate (FGT0, Well-Being Poverty Line) and Price Increases

The approximate price increases for a USD 25/tCO_2 tax and for two different tax bases are displayed in Table 4.6. Considering that the tax rate in 2014 was at USD 3.5/tCO_2, we focus on the USD 25/tCO_2 scenario as an upper bound of potential tax increases in the short term. Price changes for households are most severe for electricity, followed by motor fuel and gas. Public transport and food items are less affected by taxes on energy-related CO_2 emissions. Food prices are clearly more sensitive to taxation of N_2O and CH_4, while direct energy items are hardly affected. Generally, carbon-tax-induced price changes are less than those discussed in the previous Section on energy- and food-price changes, although the simulated tax rate can be considered non-marginal.

The first- and second-order effects are plotted in Figure 4.8, and we observe that their 95 percent confidence intervals in the calculation of average welfare effects per percentile clearly overlap. This result holds despite the fact that electricity prices are a major channel of carbon-tax-induced welfare losses and the finding of a large estimated own-price elasticity. The magnitude of electricity-price changes in the range of 9 percent does not necessarily require the estimation of demand elasticities. In Scenario I, where only energy-related CO_2 emissions are taxed, welfare effects are slightly progressive: in the range of 0.9 and 1.1 percent for lowerand higher-income households, respectively.

When CH_4 and N_2O are incorporated in the tax scheme, the welfare effects are regressive overall and particularly severe for low-income households at 2 percent of total expenditures. The much greater welfare effects are mostly caused by food price increases. Considering the inability of households to substitute away from food expenditures, this scenario has greater wel-

Table 4.5: CO_2(e) Emission Impacts, Energy Price Changes (20%)

		Electr.	Motor fuels	Gas	Publ. Transp.	Energy	Food
price change	CO_2	-4.7%	-5.9%	0.0%	0.0%	-10.8%	-2.1%
	CO_2e	-2.8%	-3.1%	-0.1%	-1.2%	-7.3%	-3.1%
+ lump-sum	CO_2	-4.5%	-5.3%	0.3%	0.7%	-9.1%	3.5%
	CO_2e	-2.6%	-2.5%	0.2%	-0.5%	-5.5%	2.4%
+ PROSPERA	CO_2	-4.5%	-5.4%	0.3%	0.6%	-9.3%	2.5%
	CO_2e	-2.6%	-2.5%	0.2%	-0.5%	-5.6%	2.0%

fare and poverty effects. These generally increase with the tax base, with a 1.1 percentage point increase in the well-being poverty rate (Table 4.7). As in the case of energy price increases, the moderate well-being poverty rate is more affected than the minimum well-being poverty rate. Redistribution via lump-sum transfers or PROSPERA can case the welfare effects to become clearly progressive. The poverty indicators even improve over all dimensions.

The short-run emission-reduction potential of consumer substitution is 5.6/3.5 (CO_2/CO_2e) percent of total household-induced CO_2/CO_2e emissions and rises to 6/4 (CO_2/CO_2e) percent in Scenario II. The taxation of CH_4 and N_2O not only leads to adverse poverty effects, but the additional short-run CO_2e-emission-saving potential is also very limited.

Table 4.6: CO_2 Intensities and Price Changes, Carbon Tax

		CI (kg/MXN)		Price Change (t = 25 USD)	
	item	CO_2	CO_2e	CO_2	CO_2e
1	Electricity	0.290	0.297	9.0%	9.2%
2	Motor Fuel	0.217	0.222	6.7%	6.9%
3	Gas	0.140	0.140	4.3%	4.3%
4	Public Transport	0.029	0.031	0.9%	1.0%
5	Food	0.020	0.070	0.6%	2.2%
6	Other	0.013	0.022	0.4%	0.7%

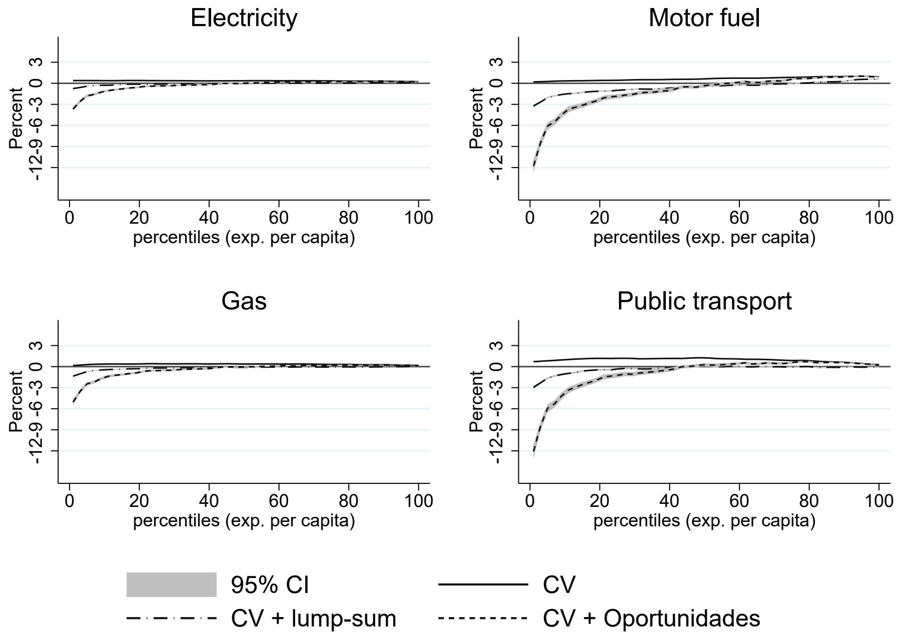

Figure 4.7: Welfare Effects, Redistribution Scenarios

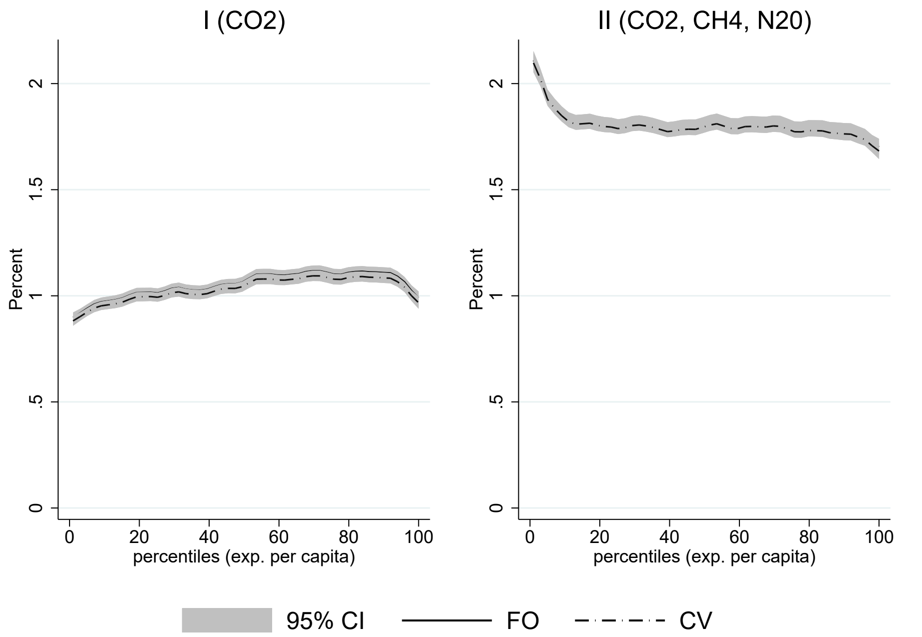

Figure 4.8: Welfare Effects of Carbon Taxes

Table 4.7: FGT Changes, Carbon Tax

		Minimum wellbeing		wellbeing	
		Tax Scenario			
	FGT	I (CO_2)	II(CO_2, CH_4, N_2O)	I (CO_2)	II(CO_2, CH_4, N_2O)
Carbon Tax	0	0.399	0.755	0.723	1.186
	1	0.140	0.264	0.392	0.651
	2	0.066	0.130	0.233	0.406
+ Lump-sum	0	-0.407	-0.607	-0.061	-0.301
	1	-0.147	-0.228	-0.189	-0.347
	2	-0.083	-0.126	-0.161	-0.272
+ PROSPERA	0	-0.407	-1.505	-0.292	-0.493
	1	-0.147	-0.633	-0.518	-0.854
	2	-0.083	-0.311	-0.446	-0.686

It is important to note, however, that these simulated emission reductions are relative to a baseline with zero income growth and tax revenues that are completely reinvested without further carbon emissions. In addition to the expected income growth, the redistribution of tax revenues to households in the form of cash transfers, tax rebates, or the increased use of public goods inevitably leads to the use of goods produced with fossil fuels if the energy system remains untransformed. In the case of direct cash transfers to households, the CO_2- emission-saving potential can shrink to 83 percent of the reductions achieved in scenarios without redistribution. If CH_4 and N_2O are taken into account, the wider tax base generates large tax revenues and lump-sum transfers, which in turn lead to large income effects and smaller CO_2 and CO_2e savings, which are reduced to 75 and 62 percent, respectively. Redistribution via PROSPERA leads to slightly larger CO_2 emission reductions, as already observed in the case of energy price changes. Considering the problematic link between taxing CH_4 and N_2O and food prices, taxing CO_2 alone provides an option for an ambitious short-run climate policy with moderate welfare effects that could be turned into welfare gains with proper redistribution schemes.

4.5 Conclusions

In this paper, we have simulated the short-run poverty and distributional effects of energy price changes and carbon taxes in a partial equilibrium framework. We have estimated a full matrix of substitution elasticities, testing first- versus second-order welfare effects and finding that the latter are only slightly different from the former, as in the case of electricity, but differ with multiple price changes. Despite this finding, two practical reasons speak against the abandonment of demand estimation in our context. First of all, assessing the validity of using first-order effects is preferable to assuming it. Second, without estimated substitution elasticities we are unable to calculate the CO_2-emission-saving potential that comes from household consumption. The latter has usually been lacking in the existing literature.

By simulating stylised price-increase scenarios, we find that only motor fuels have progressive effects. Taxing electricity, gas and public transport is regressive, although in the latter case the middle class is most affected. Also important to consider is the heterogeneity within income percentiles. For actual users with positive demand for energy items, price increases are regressive. To put energy price changes into perspective, we find that food price increases have significantly larger welfare effects. Households spend a larger percentage on food products than on energy and show limited sensitivity to prices, as reflected in a close to zero own-price elasticity. Middle-income households close to the well-being poverty line are more affected by higher energy prices than low-income households. Although the smaller effects on extreme poverty are welcome from a development perspective, the political economy behind this pattern could be problematic. The progressive distribution pattern of welfare effects resulting from a carbon tax is largely driven by private motorised transport. Though the absolute monetary losses are small for households, the public opinion on environmental policy reforms appears to be quite

Table 4.8: CO_2(e) Emission Impacts (USD 25/t CO_2(e))

		Tax Scenario	
		I (CO_2)	II (CO_2, CH_4, N_2O)
Carbon Tax	CO_2	-5.6%	-6.0%
	CO_2e	-3.5%	-4.0%
+ Lump-sum	CO_2	-4.7%	-4.5%
	CO_2e	-2.6%	-2.5%
+ PROSPERA	CO_2	-4.9%	-4.7%
	CO_2e	-2.6%	-2.4%

sensitive to gasoline-price changes.

We also simulate a carbon tax at USD 25 per t CO_2 and find slightly progressive welfare effects and substantial emissions reductions. The additional taxation of CH_4 and N_2O has the potential to create large price changes in the agricultural sector, which makes their incorporation into a carbon tax regime an unsuitable option for creating poverty and environmental synergies in short-run climate policies. Considering the problematic link between CH_4 and N_2O taxation and food prices, taxing CO_2 alone provides an option for an ambitious shortrun climate policy with moderate welfare effects that could be turned into welfare gains with proper redistribution schemes. The calculated emission reductions through energy and carbon taxes must be understood as household-consumption-induced emission reductions relative to a baseline with no income growth. Emission reductions through substitution by households can be quite substantial even in the case of small price changes. Income and related consumption growth, on the other hand, reduce the emission-saving potential. Taking into account the latter through redistribution via cash transfers, the initially large numbers become significantly smaller but remain substantial. Unsurprisingly, the redistribution of simulated tax revenue can make any regressive outcome progressive and reduce poverty. Targeted transfer through a social welfare programme (PROSPERA) proves to be preferable in terms of poverty and emission outcomes. Since compensation amounts are relatively large for lower-income households, poverty reduction through redistribution is clearly more visible at the lower, minimum poverty line and also creates fewer additional consumption effects and associated emission increases.

Eventually, the used partial equilibrium model assumes perfect pass-through of prices to consumers and no direct effects on factors of production. The absence of indirect, general equilibrium effects such as price increases for other goods than energy, makes it a special case which may only be valid in the short-run.

Chapter 5

"Stepping down the ladder": The impacts of fossil fuel subsidy removal in a developing country

5.1 Introduction

The residential sector accounted for roughly two-thirds of total final energy consumption in sub-Sahara-Africa (SSA) in 2018 (IEA, 2019). Cooking makes up the lion's share of total household energy demand and is mostly fueled inefficiently by solid biomass burnt in traditional cook stoves. The collection of wood used for cooking and for charcoal production accounts for an important share of total forest degradation on the African continent (Hosonuma et al., 2012). Further, indoor air pollution caused by cooking with woodfuels affects health, especially that of women and children (WHO, 2016). As households grow richer, they are expected to switch to modern fuels, mainly liquefied petroleum gas (LPG). To support households in this transition, governments often subsidize LPG. LPG subsidies can impose a high burden on government budgets and are likely to be regressive. This also holds for many other fossil fuel subsidies, which, in general, lead to higher greenhouse gas (GHG) emissions and may lock countries into carbon-intensive technologies. This is why fossil fuel subsidy removal has been advocated by international organizations and many developing-country governments have embarked on such reforms (Coady et al., 2018; Rentschler and Bazilian, 2017; Jakob et al., 2014b), even though many countries continue to subsidize LPG (Kojima, 2016).

The welfare impacts of fossil fuel subsidy removals and the subsequent fuel price changes

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have been subject to extensive empirical research (Arze del Granado et al., 2012; Sterner, 2011). Most studies have looked at first-order effects; that is, the incidence of welfare impacts neglecting behavioral changes. A limited number of studies have also taken into account behavioral reactions to price changes, which are important for health and environmental externalities. These studies typically draw on estimated (fuel) demand systems that exclude traditional fuel use due to a lack of reliable data (Renner et al., 2018a,b; Schulte and Heindl, 2017). This literature has provided important insights into the incidence of fossil fuel subsidies and the likely impacts of their removal. These and other studies have also examined potential complementary policies, typically advocating the use of cash-transfer systems to compensate poor households (Coady et al., 2018; Rentschler and Bazilian, 2017).

To our knowledge, quasi-experimental evidence on the impacts of energy price increases due to subsidy removals or other climate-change-related policies, which tries to causally identify behavioral reactions, is scarce and comes from developed countries (Auffhammer and Rubin, 2018; Muehlegger and Rapson, 2018; Yan and Eskeland, 2018). A related literature has investigated the impact of subsidies or other interventions intended to increase the use of cleaner cooking fuels in developing countries, particularly LPG (e.g. Imelda, 2020; Kar et al., 2019), or improved cookstoves (ICS) (e.g. Jeuland et al., 2020). The effects of subsidy removal might be different (that is, asymmetric) to those of the introduction of subsidies, due to potential reference dependence and learning effects (Fischer et al., 2019; Dupas, 2014). The scarcity of quasi-experimental evidence on the impacts of price reforms is partially due to the fact that situations with appropriate data lending themselves to such assessments are rare. We contribute to the literature with evidence from a quasi-experimental setting on the impact of subsidy removal on household cooking fuel choices in a developing country.

This paper uses cross-sectional household-survey data from Ghana collected between October 2012 and December 2013. In early 2013, the government implemented a fossil fuel subsidy reform that led to sudden price increases of about 50 percent for LPG and 20 percent for diesel. Approximately one-third of the surveyed households were interviewed before the price increases, and the remaining two-thirds afterwards; this makes it possible to rigorously evaluate the impacts of the subsidy removal on fuel choices and fuel consumption. We can investigate the impact of the reform on the choice of main cooking fuel, on charcoal consumption, and on LPG expenditure. Utilizing a survey from Ghana that took place in a different year, we can compare discontinuities in these outcomes at the reform-date cutoff point using difference-in-differences. We control for observable confounding factors to the extent possible, and provide numerous robustness checks with respect to identification assumptions.

We find that households "stepped down the energy ladder"; that is, modern fuel use decreased, and the use of transition and traditional fuels expanded. The share of households that mainly use firewood increased by three percentage points. Further, charcoal consumption in urban areas increased by about 16 percent, while the number of households considering charcoal to be their main cooking fuel decreased. We find no effect on LPG expenditure, suggesting that consumption dropped after a price increase of 50 percent. These results are robust to a number of robustness checks, including placebo regressions to investigate whether our results are driven by the survey sequence or by anticipation effects. Given the continuing general trend towards LPG adoption at the extensive margin in Ghana (WHO, 2021), we hypothesize that other forces – including income growth and learning effects – might have prevented dis-adoption at the extensive margin of consumption due to the subsidy reform. Back-of-the envelope cost-benefit calculations suggest that fiscal savings due to the reform are of similar magnitude to the welfare as well as cooking fuel choice-related social costs – including increased GHG emissions due to higher charcoal demand in urban areas, health impacts, higher expenditures, and more time needed for firewood collection and cooking.

The article proceeds as follows. Section 5.2 reviews related literature and introduces relevant concepts. In Section 5.3, we present household and price data, descriptively explore fuel use in Ghana, and discuss some identification issues. Section 5.4 describes the empirical methodology, before impact estimates are presented in Section 5.5. Section 5.6 provides robustness checks. In Section 5.7, we examine the overall costs and benefits of the introduced reform before Section 5.8 concludes.

5.2 Related literature

Our quasi-experimental study of "real world" subsidy removal in a developing-country context relates and contributes to various strands of the literature. Our findings contribute to the literature on the welfare impacts of (tax or subsidy-induced) fuel price changes. They add also to the literature on cooking fuel choices, which has learnt a lot in recent years from the study of ICS adoption. Our study is relevant to discussions about the effectiveness of LPG subsidies on enhancing adoption and about potential dis-adoption when they are reduced or abolished for climate mitigation or other reasons. Dis-adoption of modern fuels may entail adverse health and environmental impacts of fuel choices – something that we also review briefly.

5.2.1 Welfare impacts of energy price increases

International organizations, researchers, and some policy makers maintain that fossil fuel subsidies need to be abolished due to their severe adverse economic and environmental effects (Coady et al., 2018; Rentschler and Bazilian, 2017). Beyond efficiency and environmental consequences, studies on such reforms have also analyzed distributional impacts. This is because these impacts – whether due to fossil fuel subsidy removal or taxing emissions – may be ambiguous.

In Organisation for Economic Co-operation and Development (OECD) countries, lowerand middle-income households are typically more vulnerable to energy-price increases due to relatively high budget shares going to fuels (Schulte and Heindl, 2017; Flues and Thomas, 2015). In developing countries that have fuel subsidies in place, richer households capture the largest share of the subsidy, even after factoring in indirect benefits on food prices (Arze del Granado et al., 2012; Sterner, 2011). Thus, fossil fuel subsidy removal or the introduction of carbon taxes have been found to have mostly progressive effects in low-income countries, because poorer households generally have lower budget shares of carbon intensive consumer goods (Ohlendorf et al., 2021; Dorband et al., 2019). While energy price increases tend to be progressive for motor fuels, they may be regressive in some countries for other energy goods or services such as electricity, LPG, or public transport, as Renner et al. (2018a) showed for Mexico, and Renner et al. (2018b) showed for Indonesia.

Most of the studies listed here emphasize that poor, low-income households should be compensated for price reforms to mitigate their adverse effects on poverty levels and poverty intensity. Assessments of first-order price effects (that is, neglecting behavioral changes) use expenditure data and thus miss out on traditional fuel use due to data gaps. Behavioral reactions for the estimation of second-order effects are captured via estimated income and substitution elasticities. Similarly, these models typically either group traditional and/or transition fuels under “other” consumption or exclude these fuels completely due to a lack of reliable data on self-collected firewood.

5.2.2 Cooking fuel choice

Behavior is the focus of the (cooking) fuel choice literature. The “energy ladder hypothesis” postulates a regular pattern to households’ cooking fuel choice when economies develop. It posits that there exists a natural development from “traditional” fuels (firewood and agricultural waste) via “transition” fuels (charcoal, coal, kerosene) towards “modern” fuels (LPG, electricity) as a result of rising incomes (Hosier and Dowd, 1987). Each step represents an improvement in healthiness, efficiency, and ease of use.

However, this is an inaccurate description of actual household behavior (Kroon et al., 2013; van der Horst and Hovorka, 2008; Heltberg, 2004). The transition to modern fuel use has not progressed with rising incomes and urbanization at the expected pace and most households use multiple cooking fuels from different tiers of the energy ladder, a strategy referred to as “fuel stacking.” As a result of this discrepancy between theory and reality, a set of explanations have been developed for it (Ruiz-Mercado and Masera, 2015). Behavioral change happens slowly, as modern fuels may only be imperfect substitutes: traditional fires can satisfy end uses beyond cooking (such as drying clothes or disposing of waste) and they may be seen as more appropriate for the preparation of traditional meals. Other supply-and-demand factors that influence fuel use patterns include poor information (on the costs and benefits of different fuels, and their usability), credit and liquidity constraints, fluctuations in local biomass as well as modern fuel availability (and, of course, prices).

The empirical evidence on cooking fuel choices confirms significant fuel stacking and points toward the importance of household characteristics for the adoption of modern fuels or not (Muller and Yan, 2018; Ruiz-Mercado and Masera, 2015). For example, Karimu et al. (2016) examined factors that determine LPG uptake as the main cooking fuel in Ghana. Income and education are the main drivers of LPG use, as well as living in urban areas. Market factors also play a role: availability of LPG strongly predicts its use, whereas higher prices are negatively associated therewith. In an earlier systematic review of studies on the adoption of modern fuels, Lewis and Pattanayak (2012) found that socioeconomic status (mostly income and education), as well as urban location are the main predictors. A more recent literature review by Bonan et al. (2017) emphasized liquidity constraints and low willingness to pay as barriers to modern fuel adoption and stressed the importance of supply-side factors for the sustained use thereof. The recent work by Kar et al. (2020, 2019) on India's large-scale Ujjwala cooking gas program highlighted the importance of capital subsidies for LPG adoption, but also stressed the role of behavioral aspects and information vis-à-vis regular use.

Additional evidence on cooking fuel choices has been generated in the context of ICS interventions and corresponding adoption decisions (Pattanayak et al., 2019; Levine et al., 2018; Bensch et al., 2015; Bensch and Peters, 2013; Beyene and Koch, 2013; Mobarak et al., 2012). Cookstove demand tends to be highly price-sensitive (e.g. Pattanayak et al., 2019) and there is an important role played by liquidity constraints (Alem, 2021). Although stove and fuel stacking and switching is common, particularly in urban contexts (e.g. Bensch and Peters, 2013), subsidizing LPG cookstoves significantly reduces charcoal consumption in some settings (e.g. Alem and Ruhinduka, 2020).

The ICS literature has highlighted the role of prices in modern fuel adoption and fuel choices. Studies that focus on price reactions suggest that own-price elasticities of household fuels are generally negative (for a recent review, see Muller and Yan, 2018). Cross-price elasticities, on the other hand, are less well understood. While many studies have found that price increases regarding modern or transition cooking fuels increase consumption levels and/or the probability of using biomass (Alem et al., 2016; Gundimeda and Köhlin, 2008; Gupta and Köhlin, 2006; Heltberg, 2005) others have not found any such effects (Choumert-Nkolo et al., 2019; Jingchao and Kotani, 2012). Two limitations of studies of elasticities are that it is often impossible to separate income and substitution effects, and that data on shadow prices of traditional fuel use is often not available (Muller and Yan, 2018). Another occasional limitation is a lack of identifying variation in prices over time. An exception here is Alem and Demeke's (2020) study on urban Ethiopia, which found that households respond to rising kerosene prices by consuming significantly more charcoal.

When considering households' behavioral reactions to changes in fuel prices, a couple of other mechanisms should be taken into account. First, some households with low willingness to pay may adopt modern or transitional fuels because of lower (subsidized) prices and learn that the actual benefits of using the fuel exceed prior expectations (Fischer et al., 2019; Dupas, 2014). In this case, a household may continue to use the cleaner fuel even when prices rise. In contrast, anchor effects (or reference dependence) might result in dis-adoption when the latter occurs: because people anchor expectations with respect to future costs in the current subsidized prices, an increase therein at a later point in time may result in lower-willingness-to-pay effects (Koszegi and Rabin, 2006). Another price effect may be observed when prices have a signaling function, with high prices signaling a high value of use (Ashraf et al., 2010). In such circumstances, subsidies might mitigate the screening signal of prices, leading to inappropriate or infrequent use of the concerned fuel.

Empirically, the relative importance of anchoring effects vis-à-vis learning effects appears to vary from context to context. Anchoring effects have been shown to be unimportant for the continued use of, for example, improved cookstoves (Bensch and Peters, 2019), but important for the adoption of such stoves (Mobarak et al., 2012). Fischer et al. (2019) showed that anchoring effects also play a role for the continued use of curative health products, but found no evidence for learning effects, while Dupas’s (2014) findings suggest the opposite.

5.2.3 LPG-promotion policies and subsidies

To enhance the transition to modern fuels, many countries in the developing world subsidize LPG (Troncoso and da Silva, 2017; Kojima, 2016), sometimes complemented with other measures such as subsidized stoves or information campaigns too. The extent of global subsidies, calculated as the difference between consumer price and supply costs, has declined in recent years due to lower international fossil fuel prices and efforts to reform subsidies (Coady et al., 2019).[1] Kojima (2016) noted that reforms of LPG (and kerosene) subsidies are more “socially sensitive,” and hence rarer compared to price reforms of other petroleum products, coal, or natural gas. As of 2020, numerous countries had some form of targeted or universal gas and/or LPG subsidies in place. These include Algeria, Argentina, Bangladesh, Bolivia, Gabon, India, Iraq, Iran, Kazakhstan, Kuwait, Libya, Pakistan, Saudi Arabia, Turkmenistan, the United Arab Emirates, Ukraine, Uzbekistan, and Venezuela (IEA, 2021b). In some of these countries, LPG prices were raised significantly although they have remained subsidized. For example the Jordanian government raised LPG prices by around 54 percent in 2012; the Egyptian government did the same by about 100 percent in 2017 (Breisinger et al., 2019). Mexico liberalized its LPG market in 2017 (OECD, 2017); Nepal recently announced that it would remove LPG subsidies (Poudel, 2020).

[1]The subsidies covered by Coady et al. (2019) do not disaggregate those for petroleum products, and therefore cannot shed light on the extent of LPG versus gasoline/diesel subsidies.

While evidence on the effects of such subsidy removals and reductions is scarce, several studies have examined the effectiveness of various LPG-promotion programs, some of which include price subsidies, with mixed results. The cross-country comparison of LPG subsidies in Latin America by Troncoso and da Silva (2017) concluded that LPG subsidies seem to have helped the urban poor to transition to LPG, while effects have been limited in rural areas. This is in line with the qualitative assessment by Gould et al. (2018), who found that the (long-standing) LPG subsidy in Ecuador has been successful in that nearly all households consider LPG as their main cooking fuel. However, significant use of traditional fuels remains an issue in rural areas. More rigorous evidence comes from a large-scale kerosene-to-LPG conversion program in Indonesia, comprising the dissemination of a "starter kit" including one LPG cylinder and a cookstove, a subsidy on LPG, and a quantity restriction on kerosene. The program seems to have been effective in considerably raising LPG adoption, from rates of about 10 percent to about 50 percent in program areas (Imelda, 2020). India has a universal cash-back LPG subsidy, but biomass use remains widespread (Afridi et al., 2021; Kar et al., 2019).[2] Therefore, the previously mentioned Ujjwala cooking gas program in India subsidizes LPG cookstoves for poor women. With a take-up of more than 70 million in the first 35 months, the program has been very successful in raising LPG stove ownership (Kar et al., 2019).

However, despite the fuel price subsidy in place, LPG access alone has not led to households fully shifting away from traditional fuels. Kar et al. (2019) recommended incentivizing more regular use of LPG, for example through the provision of vouchers to cope with seasonal liquidity constraints. This is in line with previous work by Gould and Urpelainen (2018), who pointed to the critical role of fuel costs in the regular use of LPG. In another recent study on India, Afridi et al. (2021) found that a health-awareness campaign coupled with information on the cashback LPG subsidy increased households' monthly LPG refills by 13 percent, while Zahno et al. (2020) discovered that a health messaging intervention had an effect similar to a 10 percent price reduction on the uptake of LPG in rural India.

To our knowledge, there are only a few rare descriptive case studies on the effects of subsidy removal on fuel choices, as opposed to on the introduction of subsidies. For example, with the removal of LPG subsidy in 2008, average LPG consumption in Senegal dropped to 8.6 kilograms per capita in the same year, down from 11.7 kg per capita in 2005 (Ekouevi and Tuntivate, 2012). As of 2013, per capita consumption of LPG recovered in urban areas and average LPG consumption increased to 10–15 kg per capita (Bruce et al., 2017; Van Leeuwen et al., 2017). For Brazil, Lucon et al. (2004) reported that subsidy removal in 2001 initially led to a drop in LPG use. However, Brazil subsequently achieved a very high level of LPG adoption of around 90 percent, which Bruce et al. (2017) attributed to the consolidation of

[2] Between November 2017 and October 2018 the cashback subsidy varied between 24 and 45 percent of the final consumer price (authors' own calculations, based on Afridi et al., 2021). Note that the consumer pays the market price to the dealer and receives the cashback to their bank account within two to three days.

a gas assistance program with the conditional cash transfer scheme "Bolsa Familia" and to a well-developed LPG infrastructure, including in rural areas.

The latter finding supports the general conclusion of a World Bank policy brief by Van Leeuwen et al. (2017), which argued that investments in LPG infrastructure are a prerequisite for wide-scale adoption. Furthermore, subsidies that target the poorer segments of the population are typically needed to achieve adoption and prevent fuel stacking, ideally in combination with local awareness campaigns and schemes that distribute cookstoves for free or at lower prices. Learning effects seem occur in the case of cooking with LPG, although evidence on this is patchy at present.

5.2.4 Fuel choice impacts

There are three main reasons why governments (should) care about the choice of cooking fuel. First, the extent (and possibility) of fuel choice reactions determines the severity and incidence of welfare effects emanating from fuel price changes per market forces or government interventions. Indirect welfare effects arise from intra-household time and labor reallocations. While firewood can be collected "for free," it is mostly women and children who are responsible for this task, with detrimental effects on time spent on education, productive activities, and rest (Biswas and Das, 2022; WHO, 2016). Carrying heavy loads can also affect health.

Second, severe health effects result from indoor air pollution levels that are determined by fuel and stove-type choices. Traditional biomass cook stoves are associated with very high particulate matter concentration levels; it is estimated that indoor air pollution was responsible for more than 500,000 premature deaths in SSA in 2018 (IEA, 2019). Among the diseases associated with indoor air pollution are acute respiratory infections, stunted growth in children, pneumonia, chronic bronchitis in women, and lung cancer. For example, Imelda's (2020) impact study on the Indonesian LPG-promotion programs showed that they significantly reduced infant mortality and the prevalence of low birth weight. Furthermore, as women tend to be responsible for cooking in SSA, they are more affected hereby than men (UNEP, 2017). Much hope has been pinned on ICS mitigating negative health consequences and wasteful consumption, and many development-cooperation initiatives promote the adoption of such stoves. However, recent evidence shows that ICS do not decrease particulate matter concentration to levels that conform with World Health Organization air quality guidelines (Pope et al., 2017; Quansah et al., 2017).[3] LaFave et al. (2021) found that the use of ICS in rural Ethiopia is associated with

[3]Some have pointed out that the distribution of biomass ICS are a cost-efficient and potentially effective policy intervention in regions where outdoor cooking is prevalent and other affordable solutions are unavailable (Langbein et al., 2017). Others have suggested that the benefits of ICS fade over time, as households use such stoves irregularly or inappropriately (Hanna et al., 2016). By contrast, Bensch and Peters (2019, 2015) observed considerable effects on fuel savings and intensive use of ICS over a period of many years. They argued that ICS must be adapted to local cooking needs to avoid dis-adoption, as observed by Hanna et al. (2016).

an improvement in height-for-age of young children, although indoor fine particulate measures remain above WHO standards by an order of magnitude. Accordingly, Rosenthal et al. (2018) showed that the potential health gains of programs using LPG stoves and fuel are superior to those using improved biomass stoves.

Third, the environment is affected via both direct and indirect GHG emissions, as well as forest degradation and biodiversity loss due to woodfuel harvest (FAO, 2017). Hosonuma et al. (2012) found that woodfuel harvest, including for charcoal production, is the main driver of forest degradation on the African continent, accounting for roughly 60 percent (logging follows in second place, at about 30 percent).[4] Yet, as pointed out by Bailis et al. (2015), there is huge variation in the sustainability of woodfuels across SSA, with hotspots of unsustainable harvesting being concentrated in Central and East Africa. According to Bailis et al., 11 percent of woodfuel harvest is unsustainable in Ghana – compare that to more than 60 percent in Kenya, for example. While woodfuels thus contribute to forest degradation in Ghana, the most impactful forces there are rather agricultural expansion and mining – although quantitative evidence on the contribution of these drivers is currently patchy.[5] Further, Bensch et al. (2021) highlighted that the inefficient use of woodfuels also contributes considerably to global GHG emissions.[6]

5.3 Policy background and descriptives

5.3.1 Policy background

In late February 2013 the Ghanaian government removed fossil fuel subsidies, which led to dramatic price increases for both transport fuels and LPG. LPG prices increased by around 50 percent and diesel prices by about 20 percent, with subsequent smaller price hikes coming in later months.[7] An ex-ante study on possible impacts of the reform noted potentially adverse welfare impacts, but assumed that substitution of cooking fuels would be limited (Cooke et al., 2016). According to Cooke et al. (2016), households in the poorest quintile would have expe-

[4]Deforestation is defined here as (complete) removal of trees; that is, conversion from forest into other land uses with the expectation that forest vegetation will not regrow. Forest degradation is defined as "thinning of the canopy and loss of carbon in remaining forests, where damage is not associated with a change in land use and where, if not hindered, the forest is expected to regrow."

[5]A recent study by Acheampong et al. (2019) suggested a major role for agricultural expansion in deforestation occuring in the Ashanti region between 1985 and 2015. There is anecdotal and conflicting evidence on the drivers of the recent acceleration of deforestation in forest reserves, with reports disagreeing on the role of cocoa expansion, other commercial crops, and mining (Yoda, 2019).

[6]They calculated that the widespread adoption of ICS could lead to reductions in emissions from woodfuels with a CO_2-equivalent mitigation potential exceeding the total emissions of a medium-sized European country.

[7]None of the available sources disclose the exact date of implementation (e.g. Asante et al., 2018). We calculate the exact date of hereof as February 19, 2012, using average monthly price figures for LPG and transport fuels from the Ghana Statistical Service (2015).

rienced the strongest welfare loss, of about 2.1 percent of total income, despite capturing the lowest share of the subsidy's benefits. The authors estimated that an additional 1.5 percent of the population would be pushed into poverty.

To our knowledge, there have been no ex-post studies on the effects of the reform, but, despite the subsidy removal, the share of households relying on clean cooking in Ghana (that is, on LPG) increased from 20 percent in 2013 to 28 percent in 2018 (WHO, 2021). Therefore, we are observing a continuous increases of LPG use at the extensive margin in the aftermath of the price reform. As we will show below, this is not at odds with our findings, as aggregate statistics on the extensive margin of consumption may hide increased use of biomass fuels and decreased use of LPG at the intensive margin as a result of subsidy reform. Further, rapid (urban) economic growth in Ghana continues to drive LPG adoption. Data from the United Nations Energy Statistics Division further suggests that growth of LPG consumption per capita has halted. Between 2006 and 2012, per capita consumption rose by around 81 percent (13.5 percent annually; authors' own calculations based on UN, 2021; World Bank, 2021a). Between 2012 and 2018, however, consumption per capita decreased by around 3 percent (-0.5 percent annually).

The primary reason the government removed subsidies on petroleum products was fiscal pressure, as the budget deficit reached 12 percent of gross domestic product in 2013 (Cooke et al., 2016).[8] Ghanaian subsidies for petroleum products amounted to GHS 623 million (USD 336 million) in 2012, corresponding to about 3 percent of central-government expenditure – or about as much it puts into the country's National Health Fund (Kojima, 2016; authors' own calculations based on budget data from the Ministry of Finance, 2021). Petroleum subsidies declined very significantly to GHS 227 million in 2013 – now less than 1 percent of central-government expenditure, amounting to savings of about USD 214 million.

As a replacement for LPG subsidies, the government initiated the Rural LPG (RLP) promotion program in late 2013. Through this program, the government disseminates cookstoves and one LPG cylinder to selected rural areas with proximity to existing refilling stations and high levels of deforestation. Asante et al. (2018) found that the program had not achieved its goal of widespread LPG adoption as main cooking fuel. Many households have stopped using LPG due to high fuel costs and because of the sometimes-large distances to refilling stations. This is in line with much of the evidence presented above and supported by statistics on LPG consumption too: while LPG per capita consumption grew by around 80 percent between 2006 and 2012, it stagnated in the five years after reform.

[8]Further, as a side effect of the subsidies, LPG was increasingly used as transport fuel for taxis and other commercial vehicles due to its relatively low price compared to other transport fuels. The Ghanaian Energy Commission estimated that the transport sector accounted for around 37 percent of total LPG consumption in 2012 (Government of Ghana, 2012).

5.3.2 Household data

The main analysis of this study uses two rounds of the Ghana Living Standards Survey (round 5, and round 6: GLSS5 and GLSS6 respectively). The GLSS6 was collected between October 2012 and December 2013, meaning in the period when the subsidy reform was implemented. We use the GLSS5 data – collected between October 2005 and December 2006 – as a baseline scenario with similar seasonal fuel supply-and-demand patterns (see discussion below), but constant fuel prices. GLSS6 (GLSS5) contains 16,235 (8,313) observations at the household level (excluding those that report no cooking) and is representative at the national, regional, urban/rural, and ecological zone levels. The ecological zones comprise the Accra (Greater Accra Metropolitan Area, or GAMA), Coastal, Forest, and Savannah areas. Both GLSS followed a two-stage sampling design. In the first stage, 1200 enumeration areas – stratified by regions and rural/urban areas – were selected that form the primary sampling units (PSUs). Thus, each PSU consists entirely of either urban or rural households. In the second stage, 15 households were selected from each PSU. Each was asked to complete an expenditure diary over the course of 30 days, which was collected in five-day intervals. By the third visit – that is, after 10 days – the enumerators should have completed Part A of the household questionnaire, which includes information on the main cooking fuel. Thus, we consider a household to have been treated in GLSS6 if it was first visited 10 days or less before the subsidy reform, meaning after February 9, 2013. According to this definition, 5,556 households were interviewed before the price increase, and 10,679 afterward. For GLSS5 we apply the same time-period threshold (February 9, 2006).

Table 5.1 shows summary statistics of our outcome variables and covariates for the full GLSS6 and GLSS5 samples of both the treatment and the control group. Firewood was the dominant cooking fuel in both 2012-2013 and 2005-2006. More households consider firewood their main cooking fuel after the subsidy reform, and fewer consider either LPG or charcoal so. Yet, this is also the case in the absence of reform in 2006 (GLSS5), so likely to have (degree of) seasonality to it. Similarly, the share of households using any charcoal and average charcoal consumption are smaller for the treatment group in both surveys. Comparing GLSS6 and GLSS5, the share of charcoal users remained roughly constant over time, but consumed quantities fell. For LPG, and in line with the above observations, average LPG expenditure increased by 43 percent for the control group and 53 percent for the treatment group (that is, in comparing households surveyed after the February threshold). These overall increases are mainly driven by more users, with expenditure per user relatively constant.

From these simple comparisons we cannot determine whether the differences (or differences-in-differences) are caused by the subsidy reform or, rather, are the result of a non-random survey sequence and/or seasonal variation in fuel use patterns. For instance, the share of households in which the head is employed in the agricultural sector is much larger in the treatment group,

Table 5.1: Descriptive statistics of GLSS6 and GLSS5, treated versus control households

	GLSS6			GLSS5		
Outcomes (means, SD)	Treatment	Control	STD	Treatment	Control	STD
Main fuel: Firewood	0.56	0.50	0.11	0.64	0.56	0.15
Main fuel: Charcoal	0.26	0.31	-0.09	0.28	0.32	-0.11
Main fuel: LPG	0.17	0.18	-0.02	0.08	0.11	-0.08
Share charcoal users	0.35	0.43	-0.17	0.33	0.45	-0.24
Log charcoal consumption	1.16	1.43	-0.16	1.28	1.75	-0.24
	(1.68)	(1.79)		(1.90)	(2.06)	
Log charcoal consumption	3.31	3.31	-0.01	3.83	3.91	-0.07
(users)	(0.96)	(1.07)		(1.01)	(1.00)	
Share LPG users	0.15	0.17	-0.05	0.07	0.10	-0.10
Log LPG expenditure[x]	0.80	0.87	-0.04	0.37	0.51	-0.10
	(1.89)	(1.95)		(0.07)	(0.1)	
Log LPG expenditure[x]	5.18	5.09	0.10	5.18	5.11	0.09
(users)	(0.80)	(0.88)		(0.84)	(0.78)	
	GLSS6			GLSS5		
Covariates (means, SD)	Treatment	Control	STD	Treatment	Control	STD
Log income per capita	6.31	6.26	0.01	14.25	14.52	-0.05
	(4.96)	(5.08)		(5.37)	(5.05)	
Log HH size	1.25	1.26	-0.02	1.25	1.23	0.03
	(0.70)	(0.70)		(0.71)	(0.72)	
Number of rooms	2.22	2.29	-0.04	1.91	1.95	-0.03
	(1.64)	(1.76)		(1.23)	(1.34)	
Dwelling self-owned	0.55	0.53	0.03	0.50	0.49	0.01
HH head: Male	0.71	0.72	-0.04	0.72	0.71	0.01
HH head: Log age	3.78	3.76	0.04	3.77	3.76	0.03
	(0.34)	(0.35)		(0.34)	(0.34)	
HH-head: Log education	1.50	1.67	-0.11	1.24	1.40	-0.10
	(1.60)	(1.61)		(1.49)	(1.52)	
HH-head: Agriculture	0.46	0.40	0.13	0.66	0.62	0.09
HH-head: Unemployed	0.09	0.11	-0.07	0.23	0.31	-0.17
Main cook: Job weeks	19.61	19.59	0.00	18.67	19.44	-0.03
	(23.07)	(22.93)		(23.40)	(23.15)	
Main cook: Female	0.85	0.83	0.06	0.85	0.83	0.04
Main cook: Log education	1.25	1.34	-0.06	0.94	1.09	-0.11
	(1.54)	(1.56)		(1.39)	(1.45)	
Rural	0.57	0.55	0.04	0.67	0.53	0.04
Electricity connection	0.70	0.75	-0.10	0.57	0.69	-0.25
Road connection	0.91	0.92	-0.04	0.87	0.92	-0.17
N	10679	5556		4104	4209	

Notes: HH = household. The table presents average values, and standard deviations for nonbinary variables in parentheses. The ”STD” column reports standardized differences in means. Charcoal consumption in kg is computed by dividing total monthly expenditure by the market-level price from the price module of GLSS6, in case the market prices were retrieved in the same month. In case no local markets were surveyed in the enumeration area in the same month, we took the median price by month and district or geographical zone instead. Households reporting no cooking excluded. [x]Expenditure data for GLSS5 deflated to prices during GLSS6.

and the average years of education are lower therein too. To mitigate selection bias, we reduced the sample to districts that contain both treatment and control group households and computed weights for the latter so as to achieve balance in household-level covariates (see Section 5.4 for details).

Table 5.2: Percentage of households by region and sample

	Full sample			Rural			Urban		
	Full	Eligible	Weighted	Full	Eligible	Weighted	Full	Eligible	Weighted
Western	10.12	11.70	11.96	10.43	12.00	12.67	9.71	11.41	11.21
Central	9.54	6.26	6.70	8.99	4.86	3.08	10.25	7.63	8.88
Greater Accra	11.25	20.50	21.95	2.13	0.00	0.00	23.11	40.56	41.85
Volta	9.51	9.01	9.00	11.36	14.59	17.74	7.11	3.54	3.31
Eastern	10.89	8.15	9.64	11.09	10.17	12.00	10.63	6.17	7.52
Ashanti	11.42	10.36	10.12	8.36	0.80	0.94	15.39	19.71	19.14
Brong Ahafo	9.82	4.41	4.85	9.75	5.17	4.65	9.93	3.68	3.48
Northern	10.16	7.22	4.83	12.80	13.38	10.22	6.73	1.19	0.76
Upper East	8.81	9.70	8.90	12.44	16.67	16.40	4.09	2.89	1.54
Upper West	8.48	12.68	12.05	12.66	22.36	22.31	3.04	3.22	2.31
N	16235	7316	6917	9173	3618	2996	7062	3698	3584

Notes: Eligible households for matching are those that reside in districts with both treatment and control group households. ”Weighted” households are weighted with Entropy Balancing weights.

Due to slight sample reduction and reweighting control observations, the regional composition of the sample changes. In Table 5.2, we show the sample composition by region of the full sample, the restricted sample “eligible” for our analysis, and the weighted sample. The matching steps generally lead to an overrepresentation of households from Greater Accra and the Ashanti region in urban areas, and the Upper West, Upper East, and Volta regions in rural areas. Accordingly, the eligible and weighted samples are more urban (50 and 53 percent respectively) than the full sample (43 percent).

The changes in spatial composition when reducing the sample are associated with shifts in other household characteristics, including fuel use patterns (see Table 3) – a major determinant of a household’s reaction to the price increase. Hence our impact estimates (see Section 5.4) are not treatment effects for the entire population of Ghana, but sample-specific treatment effects. The share of households that mainly use firewood for cooking is about six percentage points lower in the weighted sample compared to the full sample before the price reform. Further, about eight percentage points more households use LPG as main cooking fuel.[9] It is difficult

[9]Fuels other than firewood, charcoal, or LPG are excluded, as they are used very infrequently. Other traditional fuels are biofuels such as crop residues or sawdust (main cooking fuel for only around 0.94 percent of all obser-

Table 5.3: Summary statistics of outcome variables and covariates for households interviewed before price reform

	Full sample			Rural			Urban		
Outcomes	Full	Eligible	Weighted	Full	Eligible	Weighted	Full	Eligible	Weighted
Fuel: Firewood	0.50	0.48	0.44	0.78	0.84	0.85	0.17	0.10	0.08
Fuel: Charcoal	0.31	0.29	0.30	0.17	0.12	0.11	0.48	0.47	0.46
Fuel: LPG	0.18	0.22	0.26	0.05	0.04	0.04	0.34	0.41	0.46
Charcoal consumption	9.55	9.56	9.41	5.30	4.43	3.84	14.79	15.02	13.58
	(19.08)	(19.29)	(19.20)	(13.12)	(12.00)	(11.27)	(23.47)	(23.62)	(22.39)
Share charcoal users	0.43	0.43	0.43	0.28	0.24	0.20	0.62	0.63	0.62
Charcoal consumption	22.10	22.46	21.87	18.81	18.86	19.37	23.95	23.89	21.81
(users)	(23.77)	(24.19)	(24.17)	(18.88)	(18.49)	(18.47)	(25.94)	(25.99)	(25.02)
LPG expenditure	21.29	25.03	28.52	5.89	3.85	4.03	40.24	47.60	52.10
	(88.23)	(85.32)	(89.00)	(50.86)	(25.92)	(23.91)	(116.34)	(115.48)	(119.30)
Share LPG users	0.17	0.20	0.24	0.05	0.04	0.04	0.32	0.38	0.42
LPG expenditure	124.39	123.32	120.56	108.80	110.28	105.38	127.68	124.59	123.38
(users)	(180.79)	(154.18)	(149.71)	(191.74)	(87.45)	(66.00)	(178.35)	(159.18)	(157.89)

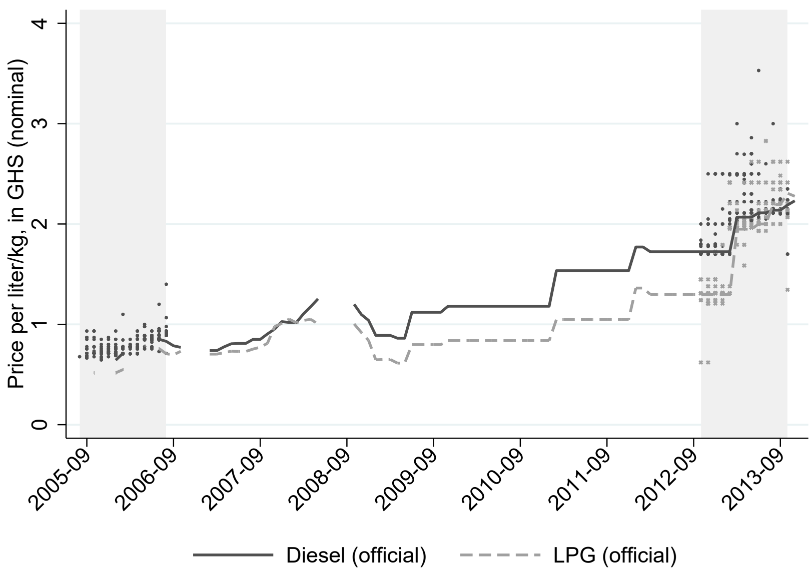
	Full sample			Rural			Urban		
Covariates	Full	Eligible	Weighted	Full	Eligible	Weighted	Full	Eligible	Weighted
Log income per capita	6.26	6.14	6.40	6.23	5.86	5.23	6.30	6.44	7.36
	(5.09)	(5.13)	(5.15)	(4.78)	(4.90)	(5.44)	(5.44)	(5.35)	(4.75)
Log HH size	1.26	1.31	1.21	1.36	1.46	1.36	1.14	1.15	1.07
	(0.70)	(0.70)	(0.70)	(0.70)	(0.67)	(0.70)	(0.69)	(0.69)	(0.68)
Number of rooms	2.29	2.46	2.23	2.50	2.87	2.61	2.04	2.02	1.88
	(1.76)	(1.86)	(1.62)	(1.92)	(2.08)	(1.89)	(1.49)	(1.46)	(1.25)
Dwelling self-owned	0.53	0.53	0.52	0.67	0.73	0.74	0.35	0.33	0.33
HH head: Male	0.72	0.74	0.69	0.76	0.78	0.75	0.68	0.70	0.64
HH head: Log age	3.76	3.77	3.77	3.80	3.82	3.83	3.73	3.72	3.72
	(0.35)	(0.35)	(0.33)	(0.36)	(0.36)	(0.35)	(0.34)	(0.33)	(0.32)
HH head: Log education	1.67	1.65	1.79	1.25	1.00	1.05	2.19	2.34	2.48
	(1.61)	(1.63)	(1.61)	(1.54)	(1.48)	(1.49)	(1.54)	(1.49)	(1.39)
HH head: Agriculture	0.40	0.37	0.35	0.60	0.61	0.68	0.15	0.11	0.05
HH head: Unemployed	0.11	0.12	0.10	0.10	0.12	0.09	0.12	0.11	0.10
Main cook: Job weeks	19.63	20.34	22.05	13.20	12.04	10.77	27.57	29.19	31.81
	(22.94)	(23.22)	(23.40)	(20.96)	(20.60)	(19.65)	(22.79)	(22.58)	(21.97)
Main cook: Female	0.83	0.84	0.84	0.85	0.88	0.87	0.81	0.80	0.82
Main cook: Log education	1.35	1.36	1.55	0.94	0.76	0.88	1.86	2.00	2.18
	(1.56)	(1.57)	(1.59)	(1.42)	(1.33)	(1.39)	(1.57)	(1.55)	(1.49)
Rural	0.552	0.516	0.465						
N	5556	3055	2862	3065	1576	1374	2491	1479	1415

Notes: HH = household. The table shows simple means and standard deviations (only for continuous variables) in parentheses. The samples consist of households in the control group. Eligible households for matching are those that reside in districts with both treatment and control group households and have non-missing values for all covariates. Matched households are those that are successfully matched, excluding estimation of the intensive margins of charcoal consumption and LPG expenditure.

to say how the change in the composition of the sample affects our estimates, which are clearly not population-wide treatment effects. However, we still believe we are looking at a relevant sample. Although it may not be representative for the Ghanaian population as a whole, it is not necessarily of less external validity for contexts with similar general socioeconomic conditions. Looking at the urban and rural samples separately, we note that the changes in the combined urban/rural samples are driven by the urban subsamples. Urban households of the weighted sample are more likely to consider LPG and less likely to consider firewood as main cooking fuel compared to the full sample. In contrast, rural households in the weighted sample are more likely to consider firewood and less likely to consider either charcoal or LPG as main cooking fuel compared to the full rural sample.

5.3.3 Prices

The 2013 spike in the official prices of LPG and transport fuel matches observed prices from the GLSS6 price survey (see Figure 5.1). While some markets / petrol stations charge significantly higher prices, many report prices close to the average official figure. After the initial price shock, there were only marginal increases therein in the subsequent months covered by the survey.



Notes: Price data were collected from the website of the National Petroleum Authority in Ghana (NPA, 2021). The graph shows the official price – averaged out across Ghana – as a line, and price observations from the GLSS price surveys as dots. The shaded areas are covered by GLSS.

Figure 5.1: Observed and official average LPG and diesel prices, 2005-2017

Transportation costs can account for a significant portion of the final sales price of charcoal,

vations). Other transition fuels include kerosene (0.17 percent of all observations). Other modern fuels include electricity (0.27 percent).

depending on the distance between production site and end-use markets. One estimate suggests that transport comprises 60–70 percent of total cost for a comparatively long distance of 300–600 kilometers (Kammen and Lew, 2005). Estimates from Ghana indicate that transport makes up 17–23 percent of total cost for charcoal produced in the Kintampo Forest District that is then transported to Kumasi, Takoradi, and Accra (Agyei et al., 2018).

Table 5.4: Do fuel prices drive charcoal prices?

	Log of charcoal price	
	(1)	(2)
Log of diesel price	0.187**	0.223**
	(0.092)	(0.090)
Ecological zone fixed effects by locality		Yes
N	831	831
R-squared	0.005	0.077

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Ecological zone fixed effects include Accra, as well as urban and rural Coastal, Forest, and Savannah zones.

Table 5.4 presents Ordinary Least Squares (OLS) regression results for the price of charcoal across 831 markets on official average diesel tariffs. Unfortunately we cannot control for transport distance, as the origin of the available charcoal is unknown, so results have to be interpreted with caution. Two different specifications are shown, the second one including location fixed effects. A 1 percent increase in diesel prices is associated with an approximately 0.2 percent rise in charcoal prices, which corresponds to the transportation costs documented by Agyei et al. (2018). Thus, removing the fuel subsidy will affect charcoal prices. Similarly, the price-of-transport increase will also affect the retail price of LPG as a function of geographic distance.

5.3.4 Seasonality

In the analysis of fuel choices, the “natural” dynamics of traditional fuel use have to be accounted for: availability might fluctuate during the year, so that the empirical analysis picks up (some) of the corresponding seasonal changes in fuel use rather than a causal effect of price increases. There is some relevant evidence on the seasonality of fuel availability in Ghana. Looking at production sites in the Bono East region (formerly Brong Ahafo), Agyei et al. (2018) found that charcoal production is highest at the start of the rainy season and lowest in the dry season. This is because it is common to fell and stack wood before the rains start, and because the key inputs grass and loose soil are easily available at the start of the rainy season. Agyei et al. (2018) also showed that periods of excessive rain disrupt the transportation of charcoal from production sites to the roads where it is supposed to be picked up before heading to the markets.

However, an in-depth countrywide study on charcoal production patterns in Ghana observed only minor monthly variation in production quantities (Nketiah and Asante, 2018) because peak rainy seasons differ between the major producing regions. In line with this assessment, Agyei et al. (2018) argued that, in urban areas, merchants are able to maintain constant prices throughout the year. Yet in rural areas prices may fluctuate more because markets are less integrated and, possibly, also due to variations in demand.

Households in Tanzania reported, for example, that they used LPG as a backup fuel for the rainy season in case it was not possible to cook outside, and when charcoal prices were high (Doggart et al., 2020). In addition, cuisine also varies between the rainy and dry seasons as staple-food production is limited during the latter (Gamor et al., 2015). This may also affect cooking fuel demand.

In sum, urban charcoal supply is less variable than may be the case in other countries but remains dependent on land transport and therefore sensitive to related fuel price increases – especially in rural areas. Therefore our analysis may pick up some seasonal supply-and-demand changes, although it is difficult to determine the direction of any potential bias. The pre-reform period covers the dry season, with its reduced supply of charcoal. The peak rainy seasons (in both the Forest and Savannah zones) fall into the post-reform period, and charcoal supply should be picking up in March/April; that is, shortly after the reform. We account for potential seasonality issues and their magnitude by using a difference-in-difference research design (details in Section 5.4.1).

5.4 Methodology

5.4.1 Causal model and difference-in-difference estimator

We use two different surveys from the same country in alternate years to estimate the treatment effect on the treated (ATT) and the conditional treatment effect on the treated (CATT) by rural/urban residence using difference-in-differences (*DiD*). In each survey, GLSS6 and GLSS5, we distinguish two periods, $t = 0$ (surveyed before and including February 9) and $t = 1$ (surveyed after February 9). Households surveyed in GLSS6 in $t = 1$ are treated, while households surveyed in GLSS5 in $t = 1$ (and $t = 0$) are untreated. In a potential outcomes framework, we denote outcomes as y_{it}^{j}, with $j = 1$ indicating a treated household i, and $j = 0$ indicating non-treated households. Of the two potential outcomes in any given period t, only one is observed. The *DiD* estimator that only uses observed expected outcomes can be written as follows:

$$
\begin{aligned}
DiD &= E\left(y_{i1}^1 - y_{i0}^0 | X_i, \text{GLSS6}\right) - E\left(y_{i1}^0 - y_{i0}^0 | X_i, \text{GLSS5}\right) \\
&= E\left(y_{i1}^1 | X_i, \text{GLSS6}\right) - E\left(y_{i0}^0 | X_i, \text{GLSS6}\right) - \left[E\left(y_{i1}^0 | X_i, \text{GLSS5}\right) - E\left(y_{i0}^0 | X_i, \text{GLSS5}\right)\right].
\end{aligned}
\tag{5.1}
$$

In cases with independent cross-sections, as here, this equation only identifies the ATT under some assumptions (Lee and Kang, 2006; Abadie, 2005). First, whether a subject was surveyed in $t = 0$ or $t = 1$ during either survey (GLSS5 or GLSS6) should be independent of households' cooking fuel choices. We assume that conditional on observable characteristics X_i, being interviewed in $t = 0$ or $t = 1$ is as good as random. In other words, there should be no unobserved factors that simultaneously influence (a) being interviewed in $t = 0$ or $t = 1$ and (b) fuel choice. One important threat to this assumption is a nonrandom survey sequence, as we discuss below.

The second identification assumption is that households surveyed during GLSS5 or GLSS6 at $t = 0$ should exhibit the same baseline response as those households in the same survey at $t = 1$:

$$
E\left(y_{i0}^0 | X_i, t = 0, \text{GLSS5}\right) = E\left(y_{i0}^0 | X_i, t = 1, \text{GLSS5}\right) \tag{5.2}
$$

and

$$
E\left(y_{i0}^0 | X_i, t = 0, \text{GLSS6}\right) = E\left(y_{i0}^0 | X_i, t = 1, \text{GLSS6}\right). \tag{5.3}
$$

That is, given covariates, we assume that expected outcomes for households surveyed in $t = 1$ would have been the same as for those surveyed in $t = 0$ – had they been interviewed in $t = 0$ as well (with this outcome non-observed). To ensure that the first two assumptions hold, we do not only control for covariates but also estimate balancing weights to construct a synthetic control group for each survey separately (details below).

Third, the *DiD* estimator identifies the ATT only if the common-trend assumption holds. We thus would expect the same difference in outcomes between $t = 0$ and $t = 1$ during both surveys if households had not been treated during GLSS6:

$$
E\left(y_{i1}^0 - y_{i0}^0 | X_i, \text{GLSS6}\right) = E\left(y_{i1}^0 - y_{i0}^0 | X_i, t = 1, \text{GLSS5}\right). \tag{5.4}
$$

Fourth, spillover effects between treated and control households may create biases (the so-called stable unit treatment value assumption, or SUTVA).

5.4.2 Specification and estimation

We estimate the following equation using the pooled GLSS5 and GLSS6:

$$y_i = \beta_0 + \beta_1 S_i + \beta_2 T_i + \delta(S_i \times T_i) + \mathbf{X_i}\beta_3 + \eta_{ds} + \epsilon_i, \tag{5.5}$$

where y_i is the outcome of interest, $\mathbf{X_i}$ is a matrix of socioeconomic and sociodemographic controls, η_{ds} are location-survey fixed effects, T_i is the time dummy indicating the time after the subsidy reform (in both GLSS5 and GLSS6), S_i indicates the survey, and δ is the parameter of interest. We cluster standard errors at the ecological zone, rural/urban, survey and treatment levels. The *DiD* estimator directly compares and tests the statistical significance of differences in fuel consumption patterns between households surveyed before and after the reform in 2013 as well as before and after the same date – but with no reform – in 2005. In our preferred specification, we estimate this equation using weighted OLS regression with entropy balancing (EB) weights (see Hainmueller, 2012), which are separately estimated for GLSS5 and GLSS6.[10]

Recently, a number of matching methods have been proposed that compute and apply weights to observations of the control group that effectively balance the average weighted covariates of treatment and control groups (see also Athey et al., 2017); thus eliminating the need to check the covariate balance. EB has several advantages over both propensity score matching as well as nearest neighbor matching (NNM) (Hainmueller, 2012). First, by incorporating covariate balance in the computation of the weights used for subsequent analyses, balance of the covariate distributions is achieved automatically for both the first and second (and possibly higher) moments. Second, in contrast to NNM where units either receive a weight of 1 (matched) or 0 (discarded), the weights computed by EB are continuous and thus retain as much useful information as possible. Third, the approach is versatile in the sense that it allows use to use the weights in a wide range of subsequent treatment effect estimators. Fourth, EB is computationally fast compared to other methods.

The weights are computed using a reweighting scheme that consists of minimizing a distance metric subject to balance and normalization constraints (for technical details, see Hainmueller, 2012). EB fails to produce weights if there exists no set of positive weights that can satisfy the balance constraints, which becomes more likely in smaller datasets and large differences across treatment and control groups. Hainmueller (2012) points out that limited overlap may lead to an extreme adjustment of base weights (which are equal to 1 for every observation by default). Large weights increase the variance of the subsequent analyses using these weights, and they imply that the analyses heavily rely on only a small share of observations in the control group to estimate the treatment effect. In our case, the inclusion of location dummies in EB results in high variance on computed weights. This is why we excluded location dummies for the computation of weights, but do include location fixed effects in all subsequent analyses.

We estimate treatment effects on several outcome variables: choice of main cooking fuel;

[10]Results from an alternative method, covariate balancing propensity score (CBPS), are presented in Section 5.6.5.

log of charcoal consumption quantities; and log of yearly LPG expenditure. For charcoal consumption quantities and LPG expenditure, we estimate treatment effects on the extensive and intensive margins of consumption, as well as a combined effect. The resulting effect on the quantity consumed is a composite of an (indirect) income and a substitution effect.[11] In our case, the prices of other consumer goods will also have increased somewhat due to higher transport costs. As we do not estimate a structural model, we cannot distinguish between the income and the substitution effects.[12]

Estimating the treatment effect on LPG expenditure relies on stronger identification assumptions. This is because expenditure on LPG is recorded in year intervals and without quantities. Thus only some months are affected by the price increase, and the treatment effect estimate will underestimate the actual treatment effect. Since households are asked to recall total LPG expenditure for the last 12 months, we also expect significant error in this variable's measurement. Hence, the noise-to-signal ratio will be higher for LPG expenditure than for the other dependent variables, and treatment effects will be harder to detect. In addition, in case households phase out LPG use at the extensive margin only after the reform, they will still report pre-reform expenditure. Hence effects on average expenditure, the intensive margin of expenditure, and especially on the extensive margin will be underestimated.

The literature has identified many determinants of cooking fuel choice (e.g. Muller and Yan, 2018). To keep a manageable set of controls, we limited the set of covariates to include proxies for every dimension of cooking fuel choice determinants: human capital, wealth and income, cultural background, bargaining power of women within the household, and local characteristics (Kroon et al., 2013). In addition to adding district fixed effects and controlling for rural/urban residence, which should hold constant local supply characteristics, we include various household characteristics that may influence preferences: household income, household size, as well as sex, age, years of education, and employment status its head. The dwelling's characteristics also influence fuel choice: that is, ownership and number of rooms have been found to predict the use of modern fuels. Moreover, it is more common in agricultural communities to rely on traditional fuels including agricultural waste. To proxy such localized characteristics more accurately, we include a dummy that equals 1 if the head considers (self-)employment in agriculture to be their main occupation. We also include two remoteness proxies for rural households: having a direct connection to a motorable road and having electricity access. Kroon et al. (2013) also found that cultural factors such as households' religious affiliation and ethnicity come with

[11] The income effect relates to changes in quantity consumed due to shifts in the purchasing power of the household, which reduces after the price increase, ceteris paribus. The substitution effect relates to changes in consumption due to relative price changes.

[12] As both diesel and LPG price changes are collinear in our sample, a structural model (e.g. a quadratic almost ideal demand system) would most likely not produce reliably identified estimates of own- and cross-price elasticities. We would also not be able to estimate the impact on firewood consumption, as we only have reliable information on firewood as main cooking fuel but not on the quantity consumed.

specific lifestyles and thus influence cooking fuel choice. We code the 64 different ethnicities reported in GLSS according to the nine larger ethnic groups in Ghana.[13]

The characteristics of the primary cook also matter for cooking fuel choice at the household level. In particular the bargaining power of the main cook, who is usually female and has a preference for clean cooking fuels and technologies, can influence the type of cooking fuel used, as well as the use of ICS (Alem et al., 2020). Therefore we included a dummy indicating whether the main cook is a woman, and the number of weeks the main cook has worked for profit in the past year. The latter serves as a proxy for bargaining power. The higher the number of weeks worked, the greater the resources controlled by the primary cook. Also, the education of the main cook may influence both the preference for clean cooking and the bargaining power within the household. We include all covariates in both the computation of weights via EB (excluding district dummies), and as controls in the subsequent weighted OLS regressions (see equation 5.5). EB weights produce highly balanced samples in which standardized differences between the treatment and control groups do not exceed 0.003, and variance ratios are well above 0.75 and well below 1.25 (and typically above 0.99 and below 1.01).

5.4.3 Identification issues

In this study, households do not self-select treatment. However, as discussed above, selection effects could be present in case certain households had a different probability of being surveyed after the subsidy reform, and if that difference is correlated with cooking fuel choices. We mitigate selection bias by including location fixed effects and by controlling for observables using matching techniques. Yet, time-variant (within each survey) unobserved factors at the location level as well as time-variant and time-invariant unobserved heterogeneity at the household level might still exist. Further, we deal with concerns about seasonality by estimating treatment effects relative to a baseline. As outlined above, the corresponding *DiD* estimator implies further identification assumptions. We discuss below the following threats to identification, and propose a series of robustness checks: a violation of the common-trends assumption, a nonrandom sequencing of the surveys (at the location, but also at the household level), anticipation effects (which would violate SUTVA), and supply shocks related to certain fuels.

First, the *DiD* specification requires seasonal variation in fuel use to be the same across the two surveys (GLSS5 and GLSS6). This common-trend assumption cannot be tested directly, and given that we use repeated cross-sections it is not possible to check for the existence of pre-trends. However there is some evidence that seasonal fuel use patterns are likely to be similar. Rainfall patterns during GLSS5 are nearly identical to to those during GLSS6 (see Figure 5.2).

Another aspect to be considered is LPG adoption: during GLSS5, LPG use was less com-

[13]These ethnic group categories are, in order of their population size: Akan, Ga-Dangme, Ewe, Guan, Gurma, Mole-Dagbani, Grusi, Mande, and Other.

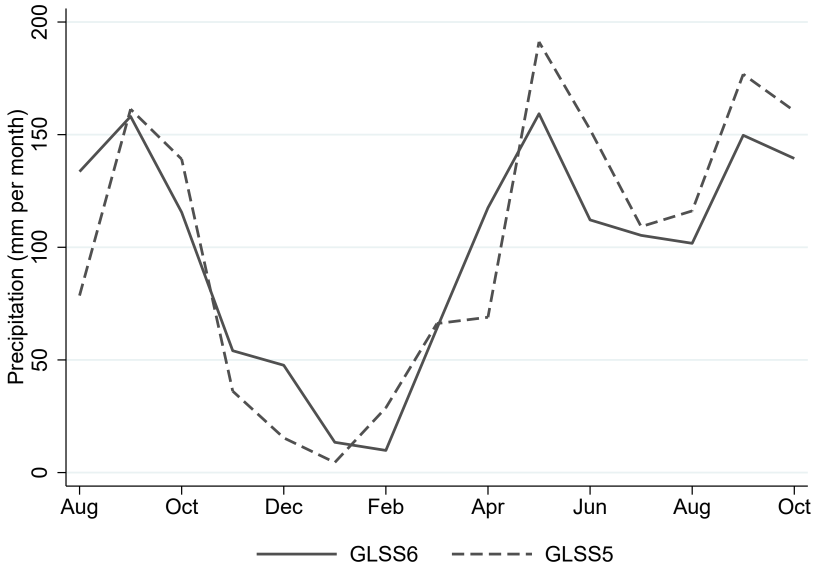
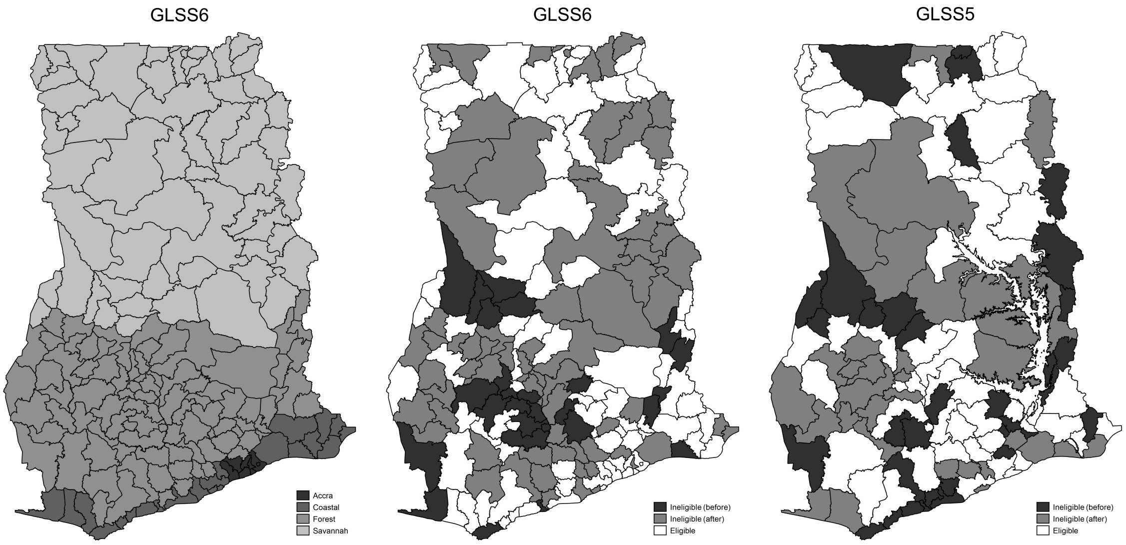


Figure 5.2: Monthly precipitation during GLSS6 and GLSS5

mon than during GLSS6. This difference may create biases if adoption rates in absence of the reform in 2013 had been higher or lower. The potential direction of bias is unclear. On the one hand, households during GLSS5 may adopt LPG at a higher rate when use is low. On the other, there may be network and supply effects causing adoption rates to (temporarily) increase with overall higher levels of adoption. We expect only small biases however. This is because, according to data collected by the WHO, the growth rate for the share of the population with primary reliance on clean cooking fuels and technology is relatively similar between the years 2006-2007 (the second year of GLSS5 and the one after) and between the years 2011-2012 (the years prior to GLSS6). Between 2006-2007, the proportion of the population with primary reliance on clean cooking fuels rose by 1.4 percentage points, and between 2011-2012 by 1.5 percentage points.

Second, the sequence of the surveys might have been nonrandom. One obvious reason why households that were surveyed late could be systematically different from those surveyed early on is the sequencing of regions or clusters, for example due to logistical reasons such as starting with more (or less) remote regions or clusters. Figure 5.3 shows a map of all districts in Ghana, distinguished by time of interview. We show districts that contain households surveyed before the price reform, districts that contain households surveyed afterward, and districts with households surveyed both before and after (labeled "eligible"). We observe that the three different district types are spatially clustered, and that those clusters are evenly distributed across the country – both north to south and east to west. Moreover, the different districts are located in all ecological zones. This suggests that the survey took place in all regions of the country simultaneously, and that the enumerators moved from one district to the next after completing



Notes: "Eligible" refers to households that are used in our analysis, that is, those households that reside in district with observations both before and after the subsidy removal.

Figure 5.3: Approximate ecological zones / Districts with sampled households before and after price increase during GLSS6 and GLSS5.

all interviews in a given location.

This spatial distribution underlines our assertion that we are looking at a relevant – and relatively representative – sample of Ghanaian districts. Yet a threat to identification comes from the sequencing of specific clusters within districts. By construction, households that are "treated" (that is, surveyed after the price reform) are more likely to have been interviewed late within the same district. The correlation between the treatment indicator and having been interviewed in the second half of the total survey period in a given district is 0.6 in the eligible sample of GLSS6. Thus, in Table 5.5, we look at differences between "late" and "early" clusters in two proxies for remoteness in rural areas: whether the village has a direct connection to a road and whether it is connected to the electricity grid.[14] Rural clusters that are surveyed late are less likely to be connected to the latter; that is, surveyors did the most remote villages last. Therefore, in addition to matching on these two remoteness proxies, we conduct robustness tests – excluding those households surveyed late in a given district – to assess whether matching on these observable proxies is sufficient to control for the nonrandom survey sequence (results presented in Section 5.6.1).

The *DiD* estimation additionally requires that there are no (unobserved) household differences due to the different sequencing of GLSS5 and GLSS6 respectively. It is reassuring that we see similar differences in household characteristics in $t = 0$ and $t = 1$ during both surveys (see Table 5.1). Further, the geographical distribution of households included in the estimation is

[14]These proxy variables come from the community questionnaire of GLSS6, and are unfortunately not available for all villages.

Table 5.5: Remoteness proxies for rural clusters, late versus early clusters

	Late	Early	Std. diff.
Direct road connection (mean)	0.92	0.93	-0.04
Electricity connection (mean)	0.71	0.81	-0.23
N	138	116	

Notes: Late clusters are those in which the majority of households were surveyed in the second half of the total survey period in the respective district.

comparable (see Figure 5.3). We also implement a more general robustness check that replaces our outcomes of interest with ones that should not (directly) be affected by the price reform (see Section 5.6.2). This exercise is meant to ensure that our results are not driven by some unobserved shock that coincides with reform (and/or correlates with the sequencing of households) and affects our outcomes of interest through channels other than behavioral reactions to the fuel price change.

Third, there may be anticipation effects. Some households may expect the price increase and make bulk purchases just before the subsidy reform. In other words the treatment affects control households, thus violating SUTVA. Such effects may concern main cooking fuel choice, monthly charcoal expenditure, and to a lesser extent yearly LPG expenditure. Thus our treatment effect estimates on main cooking fuel choice may be underestimated, and those on charcoal expenditure might be upward-biased in the presence of such anticipation behavior, as households will buy less charcoal just after the price reform. We provide results of robustness checks (section 5.6.3) in which we exclude households from the analysis interviewed around the reform's implementation date.

Lastly, the subsidy reform may also impact on the availability of fuels – in particular LPG. Such an effect would also be reflected in household fuel choices (but we cannot disentangle it from price effects). An analysis of the share of households that report that the respective fuel was "often" or "always" available suggests that LPG and charcoal availability were affected little by the reform – with the exception of urban localities in the Savannah areas, where the number of households reporting LPG availability drops to zero in the month following the subsidy reform. Excluding urban Savannah from the regressions does not affect the results (see Section 5.6.4).

5.5 Results

Figure 5.4 presents ATT estimates with 95 percent confidence intervals on main cooking fuel choice, charcoal consumption, and LPG expenditure (detailed results in Table A5.1 in Appendix A). The estimates indicate that subsidy removal caused an increase in households mainly using

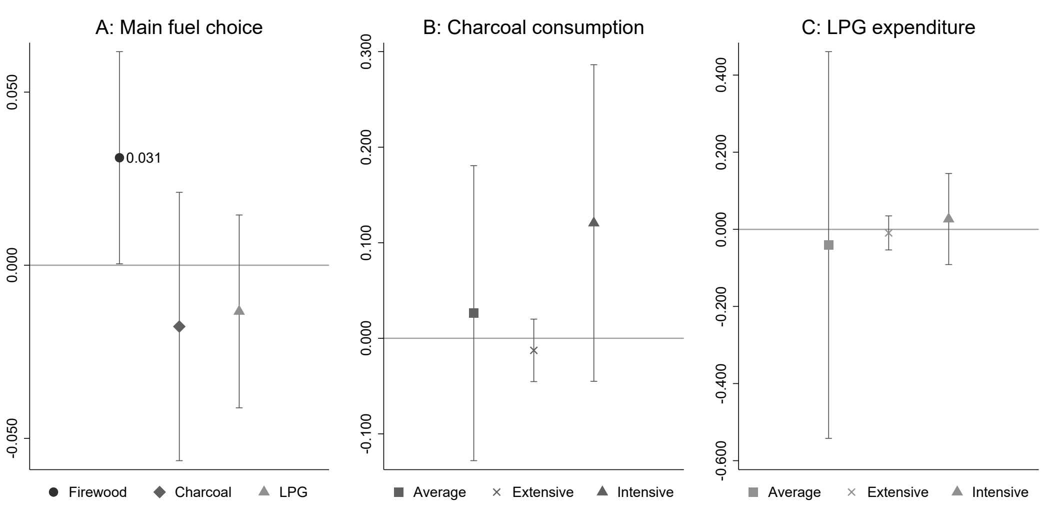


Figure 5.4: Treatment effects

firewood by 3.1 percentage points. The point estimates for the impact on charcoal and LPG use are negative but statistically insignificant. Note that if we combined charcoal and LPG into one cooking fuel category, the effect on this measure would be negative and of the same size as the effect on mainly using firewood. Hence we find that households switched away from both charcoal and LPG – that is from transition and modern fuels – toward firewood.

Results on charcoal consumption levels indicate no changes due to subsidy reform on average, but as we show below this conceals considerable heterogeneity between urban and rural areas. Likewise, we find no significant effects of subsidy reform on LPG expenditure. As discussed above, results on LPG expenditure underestimate actual adjustments. Further, nil effects on LPG expenditure imply that households reduced quantities consumed. For a price increase of roughly 50–60 percent, the average quantity of LPG consumed dropped considerably by a similar order of magnitude.

Because we expect considerable heterogeneity between rural and urban areas in terms of impacts, we look at the corresponding conditional treatment effects displayed in Figure 5.5 (detailed results in Table A5.1 in Appendix A). In rural areas, we observe cooking fuel switching after the subsidy reform. The share of households mainly using firewood increased by 5.2 percentage points (significant at the 10 percent level). Yet this result is not robust to using a different weighting method (see Section 5.6.5). We find no statistically significant effects on rural charcoal consumption. Unfortunately, the low number of rural charcoal users means that we cannot achieve covariate balance to estimate the treatment effects on the intensive margin of consumption. A look at descriptive statistics shows that rural charcoal users consumed an average of 9 percent less post-reform. In addition, we – as for the whole sample – find no statistically significant effects on average LPG expenditure.

In urban areas, the share of households that mainly use firewood increased by around 3.3

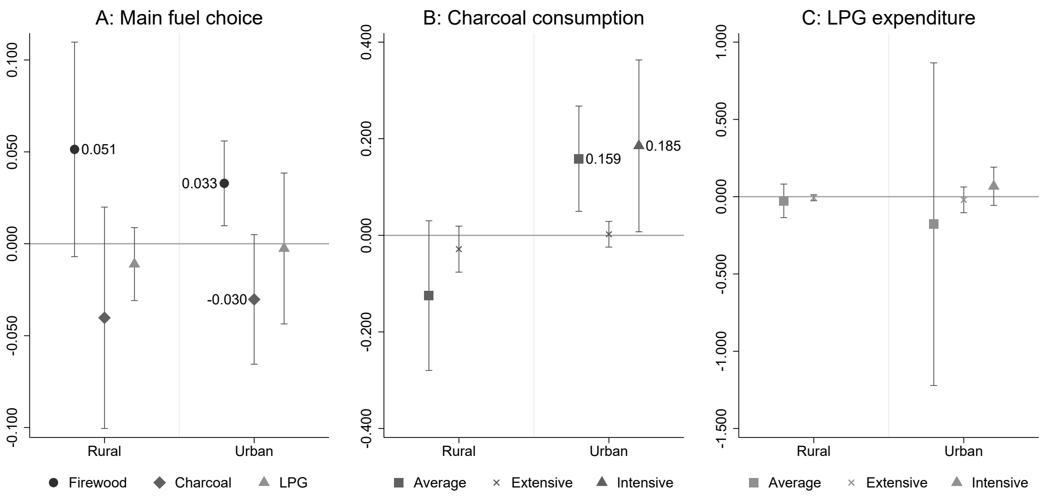


Figure 5.5: Conditional treatment effects in rural and urban areas

percentage points; the share of those mainly using charcoal decreased by 3.1 percentage points meanwhile (significant at the 10 percent level). Despite the smaller number of households that mainly use charcoal, average consumption quantities of it still increased. Households consumed 16 percent more charcoal on average, driven by increases at the intensive margin of about 18 percent (significance at the 10 percent level). Note that higher charcoal demand in urban areas probably spills over to rural areas, affecting prices and possibly production quantities – a detailed analysis of which, however, goes beyond the scope of the paper. For LPG, we find no statistically significant effects. The average expenditure effect is estimated very imprecisely compared to the estimate for rural areas, hinting at important heterogeneity in this outcome among urban households.

Taken together and carefully interpreting our estimates, we find the following reactions to subsidy removal. First, we find that urban households switched to mainly using firewood after the subsidy reform. We provide weak (that is, not robust) evidence that rural households also switched to mainly using firewood. Second, our results show a strong increase of average charcoal consumption for urban households due to increases at the intensive margin of consumption. Third, we detect no effects on LPG expenditure for urban or rural households, implying a strong reduction in the quantity of LPG used. These findings suggests that some urban households substituted charcoal for LPG while retaining the latter as their main cooking fuel. At the same time, other urban households switched away from mainly using charcoal toward mainly using firewood.

5.6 Robustness

In this Section we report results from our robustness checks, which leave all of the above key findings intact – albeit with minor qualifications. We look at potential effects of survey sequencing on our results, run placebo regressions to check for the presence of unobserved shocks, and examine the role of anticipation effects and supply-side factors. Finally, we provide estimation results using a different weighting procedure, CBPS.

5.6.1 Survey sequence

The treatment indicator is highly collinear with being surveyed late within districts. As already shown in Table 5.5 above, remoteness proxies of clusters are positively correlated with being surveyed late. Thus, to the extent that enumerators selected specific households and areas for early or late consideration, and if the selection process during GLSS6 was different to that for GLSS5, treatment effect estimates might be biased. While we match on observable remoteness proxies, unobserved confounders may still affect our results. In a robustness check for both rural and urban areas, we exclude those households that were surveyed in the last 10 percent of the total enumeration period in each district. In this reduced sample, we should find the same effects as in our main analysis above (note, however, that statistical power decreases due to sample-size reduction).

Table 5.6: CATT excluding households surveyed late

	Main fuel choice			Charcoal consumption			LPG expenditure		
	(1) Firewood	(2) Charcoal	(3) LPG	(4) Average	(5) Extensive	(6) Intensive	(7) Average	(8) Extensive	(9) Intensive
Rural	0.078*	-0.077*	-0.001	-0.340**	-0.066	–	-0.001	0.002	–
	(0.040)	(0.035)	(0.009)	(0.151)	(0.044)	–	(0.045)	(0.007)	–
N	2,565	2,565	2,565	2,565	2,565	–	2,565	2,565	–
Urban	0.030***	-0.010	-0.020*	0.145**	-0.011	0.214**	-0.155	-0.001	-0.004
	(0.007)	(0.015)	(0.011)	(0.051)	(0.010)	(0.083)	(0.404)	(0.033)	(0.052)
N	4,051	4,051	4,051	4,051	4,051	2,492	4,051	4,051	1,664

Notes: Standard errors clustered at the survey, treatment, ecological zone, and rural/urban levels. *** p<0.01, ** p<0.05, * p<0.1.

Results are reported in Table 5.6. We find similar effects when excluding households that are surveyed late. For rural areas, the effects on main cooking fuel use are a little larger, and the negative effects on average charcoal consumption and charcoal consumption at the extensive margin are significant in this reduced sample. In more remote rural places, the behavioral reactions to the reform hence appear to be somewhat more muted. The impact estimates for urban areas remain unaffected by excluding households surveyed late.

5.6.2 "Placebo impact estimates"

In the case unobserved shocks or heterogeneity drive our results, we would expect to see changes in expenditure on items that are unlikely to respond to the subsidy reform. We pick two forms of expenditure to perform "placebo regressions": education as well as clothing and footwear spending. We do not expect any effect of the subsidy reform on education expenditure other than an income effect (imperfectly controlled for by the log income per capita). For clothing and footwear, expenditure may additionally be affected by price increases vis-à-vis these goods due to higher transportation costs, but these effects should be minor.

Table 5.7: ATT and CATT, education plus clothing and footwear expenditure

	Education			Clothing & footwear		
	(1)	(2)	(3)	(4)	(5)	(6)
	ATT	Rural	Urban	ATT	Rural	Urban
Treatment	0.003	-0.383	0.271	-0.200	-0.151	-0.035
	(0.191)	(0.288)	(0.187)	(0.119)	(0.154)	(0.116)
N	10,384	4,720	4,989	10,384	4,720	4,989

Notes: Standard errors clustered at the survey, treatment, ecological zone, and rural/urban levels. *** p<0.01, ** p<0.05, * p<0.1.

Results are presented in Table 5.7. We find no statistically significant effects on education or clothing and footwear expenditure on average in the full sample, and in rural and urban areas.

5.6.3 Anticipation effects in urban areas

Households may make bulk purchases of charcoal or LPG shortly before the date of the subsidy reform's implementation. To the extent that households anticipated the latter and had the financial capability to make such purchases, this may enlarge treatment effect estimates, and thus bias our results. Therefore, we conducted another robustness check: we excluded households surveyed within a 10-day period around the defined treatment date.[15] Thus households purchasing large quantities of charcoal or LPG before the subsidy reform as well as reducing purchases right after are excluded. This can only be done for urban areas, because the rural sample becomes too small otherwise.

Table 5.8 shows treatment effect estimates in the reduced urban sample. Results look very similar to our main findings. Hence we find no evidence for anticipation effects impacting our results.

[15] Increasing the radius further would substantially reduce the sample size, such that statistical power significantly decreases.

Table 5.8: Anticipation effect placebo test results

	Charcoal consumption			LPG expenditure		
	(1) Average	(2) Extensive	(3) Intensive	(4) Average	(5) Extensive	(6) Intensive
Treatment	0.251***	0.011	0.275**	0.286	0.019	0.044
	(0.056)	(0.018)	(0.123)	(0.352)	(0.036)	(0.085)
N	3,819	3,819	2,287	3,819	3,819	1,445

Notes: Standard errors clustered at the survey, treatment, ecological zone, and rural/urban levels. *** p<0.01, ** p<0.05, * p<0.1.

5.6.4 Supply shortages

As indicated in Section 5.4.3, households in urban Savannah regions reported supply shortages of LPG after the subsidy reform. In this case, the observed changes in cooking fuel choices may be the result of supply-induced quantity restrictions rather than a behavioral response. We believe that these local shortages might be related to the subsidy reform, as higher prices and transportation costs may have impacted – at least in the short run – on the capacity of local traders and filling stations to supply LPG. However to ensure that the local supply shortages in urban Savannah – which may or may not be related to the reform – are not driving our results we exclude its households from our sample.

Table 5.9: CATT in urban areas, excluding urban Savannah households

	Main fuel choice			Charcoal consumption			LPG expenditure		
	(1) Firewood	(2) Charcoal	(3) LPG	(4) Average	(5) Extensive	(6) Intensive	(7) Average	(8) Extensive	(9) Intensive
Urban	0.019*	-0.008	-0.012	0.209***	0.012	0.157	-0.104	-0.009	0.007
	(0.009)	(0.013)	(0.019)	(0.058)	(0.015)	(0.096)	(0.475)	(0.035)	(0.067)
N	4,526	4,526	4,526	4,526	4,526	2,758	4,526	4,526	1,739

Notes: Standard errors clustered at the survey, treatment, ecological zone, and rural/urban levels. *** p<0.01, ** p<0.05, * p<0.1.

Results for the CATT in urban areas (without the Savannah region) are presented in Table 5.9. While the main findings of the previous analyses remain valid, the results do hint at some regional heterogeneity. The point estimate for mainly using firewood in the reduced sample declines to 1.9 percentage points (significant at the 10 percent level). While the effect on average charcoal consumption remains large and highly significant, the point estimate for the intensive margin of charcoal consumption is somewhat smaller and no longer statistically significant. We still find nil effects on LPG expenditure. These estimates point at some regional heterogeneity, but LPG supply shortages in parts of the country are not the main driver of our results. Further, they suggest that urban Savannah households are more likely to switch to mainly using firewood than those in other regions (possibly also due to local availability).

5.6.5 Covariate balancing propensity score

Like EB, CBPS is a procedure that computes weights for observations in the control groups to achieve covariate balance between treatment and control groups. CBPS weights are estimated using balancing moment conditions under the Generalized Method of Moments or the Empirical Likelihood frameworks (for technical details, see Imai and Ratkovic, 2014). The difference between EB and CBPS is that the latter directly models the propensity score, which is also used to construct balancing weights for observations in the control group. We present the main impact results using the CBPS weights to check whether our results are sensitive to a particular weighting scheme.

Table 5.10: ATT and CATT in rural and urban areas, CBPS weights

	Main fuel choice			Charcoal consumption			LPG expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Firewood	Charcoal	LPG	Average	Extensive	Intensive	Average	Extensive	Intensive
ATT	0.030*	-0.015	-0.015	0.048	-0.007	0.114	-0.093	-0.011	-0.013
	(0.017)	(0.023)	(0.015)	(0.075)	(0.015)	(0.083)	(0.241)	(0.020)	(0.065)
N	10,489	10,489	10,489	10,489	10,489	4,061	10,489	10,489	1,973
Rural	0.041	-0.031	-0.010	-0.070	-0.018	–	0.007	-0.001	–
	(0.029)	(0.026)	(0.009)	(0.068)	(0.019)	–	(0.048)	(0.008)	–
N	5,474	5,474	5,474	5,474	5,474	–	5,474	5,474	–
Urban	0.032***	-0.031*	-0.001	0.116*	-0.009	0.190**	-0.096	-0.012	-0.001
	(0.011)	(0.016)	(0.020)	(0.061)	(0.015)	(0.086)	(0.424)	(0.036)	(0.066)
N	5,015	5,015	5,015	5,015	5,015	3,146	5,015	5,015	1,870

Notes: Standard errors clustered at the survey, treatment, ecological zone, and rural/urban levels. *** p<0.01, ** p<0.05, * p<0.1.

Results are presented in Table 5.10. One difference to our main findings is that the effect on firewood as main cooking fuel in rural areas is no longer significant (significant at the 10 percent level in the main specification), but the point estimate changes by only 1.1 percentage points. The effects on average charcoal consumption and at the intensive margin are somewhat smaller (and significant only at the 10 percent and 5 percent level respectively).

5.7 Welfare, health, and environmental impacts

The above results suggest that subsidy reform led to an increase in the use of solid biomass fuels for cooking. This increase had health, deforestation (or forest degradation), and other negative consequences, such as increased time spent on collecting firewood or on cooking. In this Section, we provide a simple approximate assessment of the costs and benefits of the reform related to time costs, health, aggregate biomass use, GHG emissions, and aggregate fuel expenditure, which we can compare to fiscal savings.

Our analysis borrows from the methodology described in Jeuland et al. (2018) who provided a comprehensive cost-benefit assessment of clean stove and fuel adoption based on empirical studies. The following back-of-the-envelope calculations provide lower- and upper-bound estimates using the confidence intervals of our main results. These calculations are based on numerous assumptions and value judgments, and are hence "measured" with considerable uncertainty (for details, see Appendix B). Very importantly, we assume that the (sample-specific) estimated rural and urban CATTs are applicable to the whole Ghanaian population.

With these caveats in mind, we find that the increased use of biomass in urban areas amounts to about 0.33-1.12 million tons of annual wood demand for firewood consumption as well as charcoal production. In contrast, increased use of firewood and decreased use of charcoal in rural areas total a reduction of wood demand by about 0-0.22 million tons. Assuming that this additional demand is harvested unsustainably at about the same rate as reported in Bailis et al. (2015), and factoring in emission reductions from decreased LPG use, we find an increase in annual GHG emissions due to cooking fuel changes in urban areas of about 0.14-0.47 million tons of carbon dioxide equivalent ($MtCO_2e$) – or 0.4-1.3 percent of Ghana's total emissions in 2012. The additional urban GHG emissions are the result of black carbon emissions from firewood burning as well as carbon monoxide, methane, and other nonmethane hydrocarbon emissions from charcoal production and consumption. For rural areas, we find a reduction of about 0-0.16 $MtCO_2e$ – or 0-0.4 percent of Ghana's total emissions in 2012. Note that these calculations exclude potential effects of the reform on emissions from other sources (e.g. private transport).

Netting out urban and rural changes in emissions and assuming a social cost of carbon around USD 75 per ton of CO_2e, the calculated changes translate to net climate damage equal to roughly USD 0-35 million per annum. Estimated annual health costs are minor, amounting to about USD 0.45-1.86 million due to higher morbidity and, in particular, higher mortality caused by increased indoor air pollution. Time costs due to prolonged engagement in cooking and firewood collection are much greater meanwhile, estimated at about USD 7.4-59 million per annum.

Aggregate, non-monetary social costs are thus expected to be in the range of USD 8-96 million per annum. Adding estimates of the monetary costs of pricier cooking fuels – taking into account fuel switching – increases this estimate by USD 31-102 million. Higher direct costs of transport fuels (mainly diesel, without taking into account behavioral changes) amount to about USD 62 million. Transport fuel related estimated indirect household welfare effects – through higher prices of other goods and services including public transport – amount to about USD 50-88 million.[16]

Overall, cooking fuel choice-related social costs as well as direct and indirect welfare losses due to higher fuel prices result in an aggregate welfare loss of about USD 151-348 million, with a "best estimate" figure of USD 250 million. This number can be judged against fiscal savings due to subsidy removal: fuel subsidies declined by about USD 214 million between 2012 and 2013. Hence these savings are of roughly the same size (and probably a little smaller) than the annual estimated welfare and cooking-related social costs of the subsidy reform.[17]

5.8 Conclusion

This paper assesses the impact of sudden fuel price increases caused by fossil fuel subsidy reform regarding household fuel use in Ghana. LPG prices increased by around 50 percent and transport fuel prices by around 20 percent, leading to a shift in relative fuel prices. We examine this event in an impact evaluation framework, with some households being observed in a low-price environment and others in a high-price one. While LPG prices increased both directly via tariff and indirectly via transport price hikes, charcoal and marketed firewood prices increased only indirectly depending on transport distance from the production site, while the cost of collected firewood for own consumption arguably remained constant. Hence not only did cooking fuel become more expensive, but the price of modern fuels, here LPG, rose relative to transition and traditional ones.

We have shown that many households "stepped down the energy ladder" in response to subsidy reform; they moved from modern and transition fuels to transition and traditional ones instead. Three main findings stand out from our estimates that we subjected to a series of robustness checks. First, the overall share of households who mainly use firewood for cooking increased by about three percentage points. In rural areas, this share increased by about five percentage points as households switched away from charcoal. This rural effect is not very precisely estimated, and not robust to the weighting procedure. The share of urban households mainly using firewood increased by about three percentage points – a more robust result.

Second, average charcoal consumption in urban areas rose by around 16 percent, while

[16]As we assume inelastic transport fuel demand, there are no related environmental externalities by assumption.

[17]Note that environmental damages arising from unsustainable wood collection other than GHG emissions are not reflected in our estimates. Again, these costs are small compared to the ones included in the analysis, and are potentially outweighed by prospective welfare gains achieved through reduced capital and maintenance costs for modern stoves (Jeuland et al., 2018).

we find weak evidence that the number of households considering charcoal as main cooking fuel decreased by three percentage point – indicating a concentration of charcoal consumption. That is, some households switched away from charcoal, while others increased its use to such an extent that the net effect on total consumption was positive. Third, impact estimates suggest that LPG expenditure remained constant after a 50 percent price increase, indicating that quantity consumed dropped. Given the simultaneous increase in average charcoal consumption, we assume that some households substituted charcoal for LPG at the intensive margin. Note that our estimates likely underestimate the true effect of the reform on LPG expenditure. Hence, the (short-term) impact on LPG expenditure might even be higher, in fact.

The findings suggest that subsidy reform led to substitution of charcoal for LPG in urban areas, and hence to significantly lower levels of the latter's consumption – even despite a general trend toward higher LPG adoption at the extensive margin in Ghana (WHO, 2021). Given that growth in LPG per capita consumption in Ghana was stagnant between 2012 and 2018, we believe that the effects of the reform are quite persistent. It is likely that a combination of rising incomes, learning effects, and other policies aimed at increasing clean fuel use prevented widespread dis-adoption of LPG in the wake of subsidy reform, although we cannot test this hypothesis directly.

Our estimates are not treatment effects for the entire population of Ghana, but sample-specific treatment effects. As we have explained, our various GLSS sub-samples are not representative of the Ghanaian population. However we do believe they are relevant samples in that they reflect some of the characteristics of numerous developing economies, for which the potential effects of subsidy removals are a relevant policy issue. These characteristics include socioeconomic characteristics as well as fuel use patterns, particularly fuel stacking in a context where an important and often increasingly large segment of the urban population uses modern fuels, while traditional fuels prevail in rural areas.

Our results show that fossil fuel subsidy removals can lead to important adjustments in household fuel choices. These adjustments and their harmful implications need to be considered when planning to remove subsidies, especially in light of recent evidence that high prices remain a barrier for LPG adoption – even in regions where targeted interventions were implemented (Kar et al., 2019; Asante et al., 2018; Gould and Urpelainen, 2018). The costs and benefits of (targeted) LPG subsidies need to be evaluated carefully. This is clearly demonstrated by an approximation of the costs of the reform. Our estimate of increased GHG emissions, health impacts, higher fuel prices, and greater time spent on firewood collection and cooking (around USD 250 million annually) are of a similar order of magnitude to the fiscal savings (about USD 214 million) from subsidy removal. In addition, this reform has most likely increased some important components of Ghana's GHG emission levels due to higher charcoal demand in urban areas. Instead of simply cutting fossil fuel subsidies, better context-specific climate policies should try to avoid such negative "side effects." Where traditional and transitional fuels are potential substitutes, well-targeted LPG subsidies may be justified to improve access to clean fuels and cooking technology. Further, fossil fuel subsidy reform could be accompanied by targeted compensatory transfers as well as measures to prevent dis-adoption of modern fuels, for example information campaigns.

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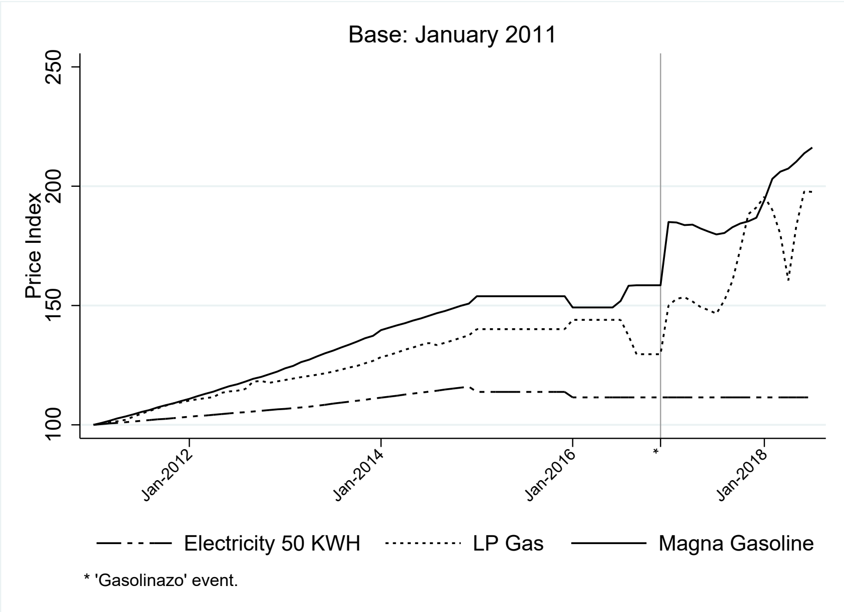
Appendix to Chapter 2

A: Energy price development in Mexico City



Notes: Self-elaboration based on data from CFE (2017); Gobierno de México (2017); PEMEX (2017)

Figure A2.1: Energy price indexes for Mexico City, 2011–2018

B: Price data

Fuels The ENAMIN survey aggregates all LPG, natural gas, gasoline, coal, and ”others” into a single category. Given that it is not possible to observe fuel-inputs at a more disaggregated level, we cannot assign the exact price to the ”Fuels” category. As the largest share within that category is expected to be gasoline, we approximate the real price with gasoline prices. The price of gasoline corresponds to the simple average between high- and low-octane gasolines. We additionally estimate the cost-function for LPG prices as well as an unweighted average of gasoline and LPG prices, yielding almost identical elasticity estimates (results not reported).

Electricity Total electricity consumption in kWh is estimated by matching electricity prices with the survey data on firms' expenditure. As most firms are not officially registered with tax authorities, we assume that informal and self-employed entrepreneurs receive bills for residential rather than commercial customers. For formal firms that hire labor, we assign the PBDT (Pequeña Demanda en Baja Tensión) tariff, denoting small demand at low voltage (up to 25 kW). We consider the fact that the electricity cost structure follows an increasing block tariff. The available data provides us with monthly average prices at different levels of consumption for 46 cities for the residential tariff. Therefore, regional and seasonal fluctuations are captured. In warmer climate regions, for example, tariffs are separated into summer and non-summer rates, mainly due to air-conditioning costs. To estimate quantities of electricity consumption, we follow several steps. First, the official price levels are assigned to all firms operating in the cities under consideration. MSEs based in small cities or in rural areas are assigned the average price that is prevalent in their respective federal state. Second, the block-price structure is considered by assigning the average electricity price that corresponds to expenditure. This procedure makes it possible to convert the values into prices per kWh and estimate the amount of electricity that the firm consumes each month. It is possible that MSEs receive electricity from households or other firms near the places they typically operate. In this case it could be that they pay a premium for electricity, which would introduce an upward bias to the kWh estimate. For larger, formal firms, we assign the national average of the PBDT tariff, as regional data is not available. We are able to assign each firm the respective tariff of the PDBT block structure, and thus the respective block price accordingly. For those firms that clearly do not contract the PBDT tariff (as indicated by negative kWh consumption values when computing real consumption with the expenditure and price data), we assign the residential tariff instead.

Labor Based on the workers' information reported in ENAMIN, we construct a price measure by computing the median wage for 10 industries (construction, manufacturing, miscellaneous services, personal services, professional services, repair services, restaurants and hotels, retail and wholesale trade, transportation services, other) and 75 municipalities. The 46 main cities are considered independently, while the remaining geographical locations correspond to the surrounding rural areas of each federal state.

C: Input-demand elasticity estimation

The translog function as developed by Christensen et al. (1973) provides enough flexibility to approximate any function to the second degree and imposes restrictions on substitution elasticities. The empirical approach is similar to the recent studies of Haller and Hyland (2014) as well as Bardazzi et al. (2015). The cost-function is defined as follows:

$$\begin{aligned} ln(C_f) = &\beta_0 + \sum_{i=1}^{n} \alpha_i ln(p_{if}) + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\beta_{ij} ln(p_{if}) ln(p_{jf}) \\ &+ \sum_{i=1}^{n} c_i ln(p_{if}) ln(y_f) + \gamma ln(y_f) + \beta_Z Z_f + \beta_D D_f + \mu_f \end{aligned} \tag{A2.1}$$

Where f is the firm index, i and j are production inputs, C is cost, p are prices, y is output, Z are additional explanatory variables, and D_f dummies – including region, industry, and time dummies – as well as μ_f (firm specific error terms). By differentiating equation A2.1 logarithmically with respect to price, we obtain the factor-share equations:

$$S_{if} = \alpha_0 + \sum_{j=1}^{n} \beta_{ij} ln(p_{if}) ln(p_{jf}) + c_i ln(p_{if}) ln(y_f) + \mu_f \tag{A2.2}$$

We estimate equations A2.1 and A2.2 simultaneously using the two-step seemingly unrelated regression (SUR) method developed by Zellner (1962) using generalized least squares (see parameter estimates in Table A2). SUR allows errors u_f to be correlated across equations for each observation. Thus, we account for the interdependence of the use of different inputs and total costs. Motivated by production theory, we impose symmetry and linear parametric constraints across both equations. Hence, parameter estimates of the same α, β, and c_i in equations A2.1 and A2.2 are forced to be equal.

Own-price elasticities (equation A2.3) measure the average percentage change in demand for input i given a 1 percent price increase. Cross-price elasticities (equation A2.4) are absolute measures of substitutability, giving the percentage change in demand for input i when the price of another input j rises by 1 percent.

$$\eta_{ii} = \frac{\gamma_{ii} + S_i^2}{S_i} - 1 \tag{A2.3}$$

$$\eta_{ii} j = \frac{\gamma_{ij} + S_i S_j}{S_i} \tag{A2.4}$$

Before computing elasticity estimates, we undertake several tests to evaluate whether the cost-function produces reliable results. Following Haller and Hyland (2014), we first compare predicted with actual cost shares. The sample means of the two variables are nearly identical.

Second, the cost-function should satisfy monotonicity, resulting in nonnegative predicted cost shares. For instance, for the sample containing only firms employing labor, 4.7 percent of observations exhibit negative predicted electricity cost-shares. These observations are dropped before estimating elasticities. Finally, the cost-function should satisfy quasi-concavity, which means that the Hessian matrix is negative semi-definite: that is, own-price elasticities should be negative at the mean of the sample. For our case, some electricity elasticity estimates do not satisfy quasi-concavity (26 percent of observations), possibly due to incorrectly modeling of the cost structure of the block tariff. To produce more reliable estimates, we iterate the estimation in the following way: after each estimation, observations violating monotonicity and quasi-concavity are dropped and SUR is estimated again. This procedure is repeated until none of the observations violate monotonicity or quasi-concavity. Although the sample size decreases substantially, elasticity estimates do not differ to the extent that the qualitative findings change, particularly with respect to the labor-energy substitution relationship. This indicates that we do not systematically bias the estimation by reducing the sample.

Table A2.1: Parameter estimates of the translog cost-function estimation

Dependent: Log costs	All industries, hired labor		All industries, self-employed	
Log electricity price	0.35***	(15.59)	0.18***	(3.34)
Log fuels price	0.23***	(5.36)	0.31***	(3.52)
Log wage rate	0.42***	(9.86)	0.50***	(4.75)
Interaction of log prices (electricity)	0.05***	(9.52)	0.03***	(8.60)
Interaction of log prices (fuels)	-0.02**	(-2.74)	-0.03***	(-6.55)
Interaction of log prices (wages)	-0.02*	(-2.55)	0.06***	(7.95)
Interaction of log prices (elec. and fuels)	-0.03***	(-5.48)	0.00	(0.16)
Interaction of log prices (elec. and wages)	-0.01	(-1.93)	-0.03***	(-7.40)
Interaction of log prices (fuels and wages)	0.03***	(5.24)	-0.03***	(-6.07)
Interaction of log elec. prices and log output	0.00	(0.94)	0.01	(1.07)
Interaction of log fuel prices and log output	0.02**	(2.88)	0.02	(1.66)
Interaction of log wage rates and log output	-0.02***	(-4.48)	-0.02*	(-2.10)
Log output value	0.25***	(16.54)	0.11***	(3.33)
Age of owner	0.02**	(3.23)	0.00	(0.03)
Age of owner squared	-0.00***	(-3.40)	0.00	(-0.25)
Female entrepreneur (dummy)	-0.08*	(-2.52)	-0.06*	(-2.33)
Age of the enterprise	0.00	(-0.34)	0.00	(1.04)
Log years of schooling	0.01**	(2.78)	0.00	(0.47)
Firm has premises (dummy)	0.10*	(2.48)	0.16***	(6.28)
Entrepreneur is self-employed (dummy)	-0.24**	(-2.82)	-0.02	(-0.99)
Capital stock	0.00***	(9.11)	0.00	(0.85)
Dummy unpaid labor	0.03	(0.81)		
Intercept	4.04***	(20.45)	5.60***	(12.41)
Ratio of variable fuels costs				
Log electricity price	-0.03***	(-5.48)	0.00	(0.16)
Log fuels price	-0.02**	(-2.74)	-0.03***	(-6.55)
Log wage rate	0.03***	(5.24)	-0.03***	(-6.07)
Log of output value	0.00	(-1.63)	0.01***	(5.11)
Ratio of variable electricity costs				
Log electricity price	0.00	(-1.63)	0.01***	(5.11)
Log fuels price	-0.03***	(-5.48)	0.00	(0.16)
Log wage rate	-0.01	(-1.93)	-0.03***	(-7.40)
Log of output value	-0.01***	(-10.37)	-0.00**	(-3.09)
Ratio of variable wage costs				
Log electricity price	-0.01	(-1.93)	-0.03***	(-7.40)
Log fuels price	0.03***	(5.24)	-0.03***	(-6.07)
Log wage rate	-0.02*	(-2.55)	0.06***	(7.95)
Log of output value	0.02***	(7.15)	-0.01*	(-2.30)
Dummy unpaid labor	-0.01	(-1.60)		
N	1758		1363	

Notes: Significance levels: * p<0.1, ** p<0.05 *** p<0.01. T-statistics in parentheses. Year, region, industry, and block-tariff dummy variables are included in all equations, but parameter estimates are not reported.

D: Elasticity estimates by sector

Table A2.2: Own- and cross-price input-demand elasticities, retail and wholesale trade

	Price of fuel	Price of electr.	Price of labor
Firms with hired labor			
Fuels	-0.97***	0.04	0.88***
Electricity	0.06	-0.39***	0.35***
Hired labor	0.32***	0.08***	-0.40***
Self-employed			
Fuels	-1.09***	-0.04	1.02***
Electricity	-0.06	-0.63***	0.70***
Own labor	0.08***	0.04***	-0.11***

Notes: Significance levels: * p<0.1, ** p<0.05 *** p<0.01. T-statistics and resulting significance levels are computed using the delta method. Elasticity estimates are obtained after the fourth iteration for hired labor and after the seventh for one-person firms. This reduced the sample size from 438 to 279 and from 727 to 446 respectively.

Table A2.3: Own- and cross-price input-demand elasticities, services

	Price of fuel	Price of electr.	Price of labor
Firms with hired labor			
Fuels	-0.84***	-0.10**	0.77***
Electricity	-0.24**	-0.42***	0.76***
Hired labor	0.22***	0.09***	-0.31***
Self-employed			
Fuels	-1.02***	0.06*	0.84***
Electricity	0.29*	-0.75***	0.58***
Own labor	0.09***	0.01***	-0.10***

Notes: Significance levels: * p<0.1, ** p<0.05 *** p<0.01. T-statistics and resulting significance levels are computed using the delta method. Elasticity estimates are obtained after the seventh iteration for hired labor and after the second for one-person firms. This reduced the sample size from 1,032 to 636 and from 1,403 to 1,369 respectively.

Table A2.4: Own- and cross-price input-demand elasticities, manufacturing

	Price of fuel	Price of electr.	Price of labor
Firms with hired labor			
Fuels	-0.80***	0.01	0.72***
Electricity	0.04	-0.44***	0.59***
Hired labor	0.31***	0.08***	-0.40***
Self-employed			
Fuels	-1.06***	-0.06	0.49***
Electricity	-0.20	-0.47***	0.24*
Own labor	0.07***	0.01*	-0.08***

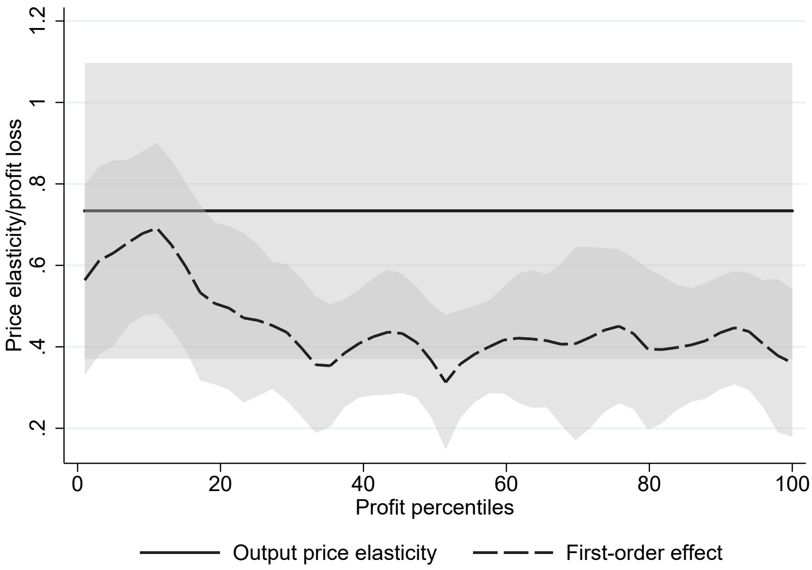
Notes: Significance levels: * p<0.1, ** p<0.05 *** p<0.01. T-statistics and resulting significance levels are computed using the delta method. Elasticity estimates are obtained after the sixth iteration for hired labor and after the tenth for one-person firms. This reduced the sample size from 787 to 600, and from 1,074 to 862 respectively.

Table A2.5: Own- and cross-price input-demand elasticities, restaurants and hotels

	Price of fuel	Price of electr.	Price of labor
Firms with hired labor			
Fuels	-0.82***	-0.05	0.81***
Electricity	-0.11	-0.46***	0.60***
Hired labor	0.29***	0.09***	-0.38***
Self-employed			
Fuels	-1.17***	-0.09	0.61***
Electricity	-0.18	-0.19	0.43***
Own labor	0.05***	0.02***	-0.07***

Notes: Significance levels: * p<0.1, ** p<0.05 *** p<0.01. T-statistics and resulting significance levels are computed using the delta method. Elasticity estimates are obtained after the fourth iteration for hired labor and after the seventh for one-person firms. This reduced the sample size from 589 to 451 and from 1,054 to 404 respectively.

E: Output price transmission versus first-order profit loss



Notes: Output price elasticity from specification (3) in Table 2.5 of the main text, with 95% confidence interval.

Figure A2.2: Profit loss estimates and output price elasticity for taco, tamales, and tortilla producers

Appendix to Chapter 3

A: Additional Tables and Figures

Table A3.1: Summary statistics by generator use, full sample (2000–2015)

	Generator user			No generator user		
	Mean (1)	Median (2)	SD (3)	Mean (4)	Median (5)	SD (6)
Capital (B IDR)	7.56	0.80	53.43	1.64	0.18	7.97
Total sales (B IDR)	11.62	1.49	28.81	2.86	0.31	9.82
Value added (B IDR)	4.53	0.55	15.51	1.20	0.11	7.47
Number of workers	298.55	96.00	723.65	112.72	35.00	319.18
Value added per worker (M IDR)	16.62	4.97	57.33	7.96	2.79	34.64
Electricity (GWh)	2.14	0.16	13.23	0.46	0.01	2.93
Electricity, purchased (GWh)	1.24	0.07	6.83	0.46	0.01	2.93
Electricity cost share	0.04	0.01	0.07	0.03	0.01	0.07
No. of generators	1.76	1.00	1.32			
Capacity of generators (kVA/kW)	489.64	250.00	626.84			
Electricity, self-generated (GWh)	0.91	0.00	10.83			
Energy intensity (GJ per VA)	10.98	4.54	19.43	6.83	2.83	11.80
CO2 intensity (kg per VA)	815.29	339.64	1430.06	512.28	211.17	884.89
Sectoral electricity sensitivity	0.58	1.00	0.49	0.50	1.00	0.50
No. observations	53,426			143,299		

Notes: All monetary values are in billions (or millions) of Indonesian Rupiah (in 2000 prices). Capital stock, sales, energy and CO2 intensity are winsorised at the 1st and 99th percentiles by year and generator ownership. Self-generated electricity computed as difference between total electricity consumption and purchased electricity. Energy intensity of primary energy consumption (electricity and fuels), self-generated electricity included indirectly through fuel consumption. The measure of energy intensity of grid electricity assumes identical efficiency of electricity production (by fuel) between PLN and independent providers. kWh produced by renewable sources is directly converted to MJ. CO_2 emissions are calculated per fuel input using appropriate conversion factors.

Table A3.2: Standardized differences in means, unmatched and matched samples

	Unmatched sample		Matched sample	
	STD	VAR	STD	VAR
	(1)	(2)	(3)	(4)
log Capital stock	0.13	2.58	0.02	1.63
log No. of workers	0.29	3.23	0.01	1.09
Observations	61,643		49,394	

Notes: STD = Standardized difference in means; VAR = variance ratio. Matched sample is the estimation sample of equation 3.1 with *log* total sales as dependent variable.

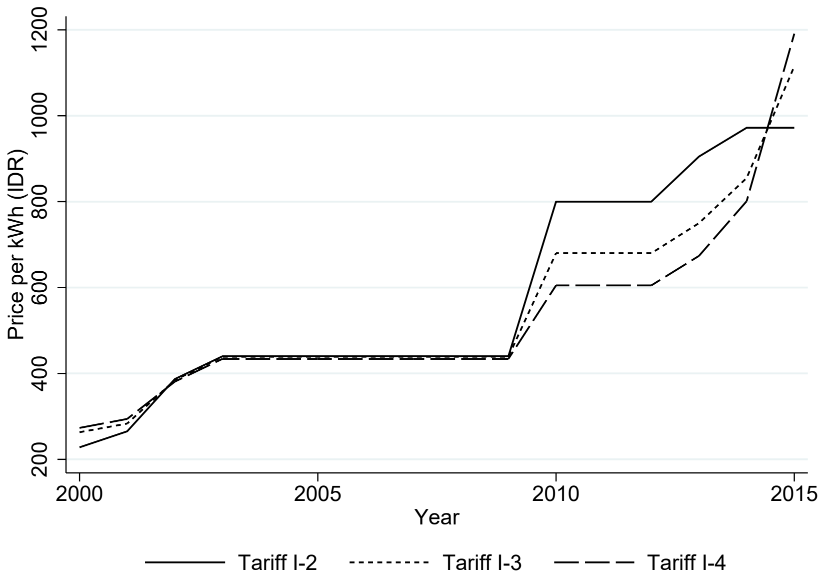
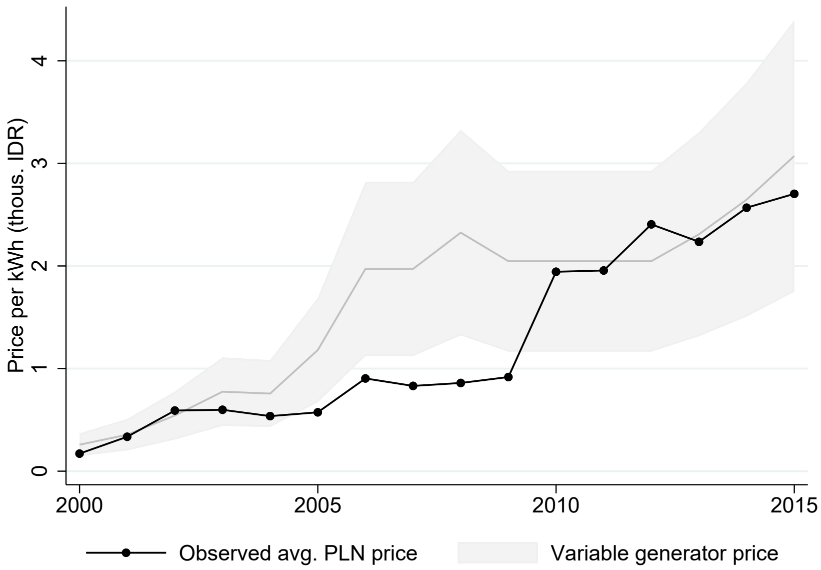


Figure A3.1: Electricity tariffs by category, 2000–2015



Notes: Fuel use data taken from `https://www.generatorsource.com/Diesel_Fuel_Consumption.aspx` indicate that generators operate at between 0.261–0.656 litres per kWh, depending on the load factor and generator size. We use these figures to compute the lower and upper bounds of variable costs per kWh.

Figure A3.2: Electricity costs, grid versus generator, 2000–2015

B: The environmental impact of generator use

Calculating emission intensities

The tier 1-method proposed by IPCC (2006) to compute emission intensities per kWh requires data on the amount and types of fuels combusted for electricity generation and default emission factors for each fuel. We take emission factors from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, and fuel consumption data from PLN statistical yearbooks. Table A3.3 shows the fuel categories reported by PLN, the matched fuel categories taken from IPCC, as well as the default emission factors of the greenhouse gases carbon dioxide, methane and nitrous oxide for stationary combustion in the energy industries. For coal, we used the conversion factor for the sub-bituminous variant, as this is the type mainly used for domestic supply in Indonesia (ERIA, 2019).

Table A3.3: Fossil fuel categories and emission factors

		Emission factors per TJ		
PLN fuel category	IPCC fuel category	CO_2	CH_4	N_2O
Diesel fuel (*Solar*)	Gas/diesel oil	74100	3	0.6
Industrial diesel oil	Gas/diesel oil	74100	3	0.6
Marine fuel oil	Residual fuel oil	77400	3	0.6
Coal	Sub-bituminous coal	96100	1	1.5
Natural gas	Natural gas	56100	1	0.1

We cannot include the use of lubricants in the emission intensity calculation because lubricant use is reported by PLN for only a few years. This omission, however, hardly matters: For instance, in 2005 PLN reports the amount of lubricant use and it only contributes about 0.03 percent to the total emission from fuel combustion. Further, we do not observe fuel inputs for electricity provided by independent producers. We estimate the energy content assuming that these providers operate under similar conditions as PLN, that is, we assume that fuel consumption per kWh is the same for both PLN and independently provided electricity. We use the default emission factors for stationary combustion in manufacturing industries (which are the same for the fuel categories reported in Table A3.3) to calculate the emission intensities of direct fuel use at the firm-level.

Figure A3.3 plots the calculated emission intensity per kWh of Indonesia's electricity generation, as well as the emission intensity of the European Union (EU) for comparison, taken from the European Environment Agency.[18] Indonesia's energy mix is more emission intensive by a factor of between 1.37 in 2000 and 2.73 in 2015. The gradual increase in Indonesia's

[18]National emissions reported to the UNFCCC and to the EU Greenhouse Gas Monitoring Mechanism, available at `https://www.eea.europa.eu/data-and-maps/data` (accessed September 16, 2021).

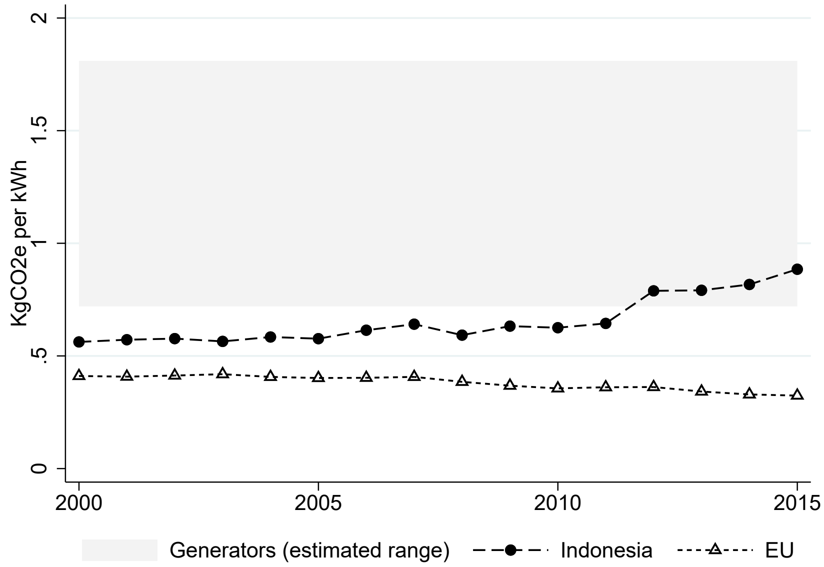


Figure A3.3: GHG emissions per kWh, 2000–2015

emission intensity is due to the expansion of coal-fired capacity: While the share of electricity generated by coal plants was roughly 36 percent in 2000, it increased to 53 percent in 2015 (with the largest increase between 2011 – 2012). The Figure also shows an estimated range of the emission intensity of generators. We convert fuel use estimates of generators to emission intensities using the emission factors for diesel fuel from above. The estimated range does not include emissions from lubricant use. Before Indonesia's energy system became even more reliant of coal in 2012, generator use is clearly associated with higher GHG emissions. The same is true for the years after 2012, however the GHG emissions of grid electricity entered the range of possible emission intensity of electricity produced by diesel generators. However, we expect that average emission intensity of electricity from generators among Indonesian firms has remained higher than that of grid electricity, since not all firms will operate with perfectly efficient diesel generators.

The emission intensity of generator using firms

We estimate the environmental impact of using generators at the firm level using a simple regression specification. We regress the energy and emission intensity measures on contemporary generator use. Controls include the (log of) total output, capital stock, number of workers and material inputs value. We also include district-year and 5-digit-sector-year fixed effects. We do not, however, include firm fixed effects, since then we would only measure the influence of changes in generator use on the intensity measures. We also compute balancing weights in order to compare similarly-sized firms to each other. The resulting estimate should reflect differences in average energy and emission intensities of similar-sized firms in the same, narrowly defined

Table A3.4: Results for energy and emission intensities

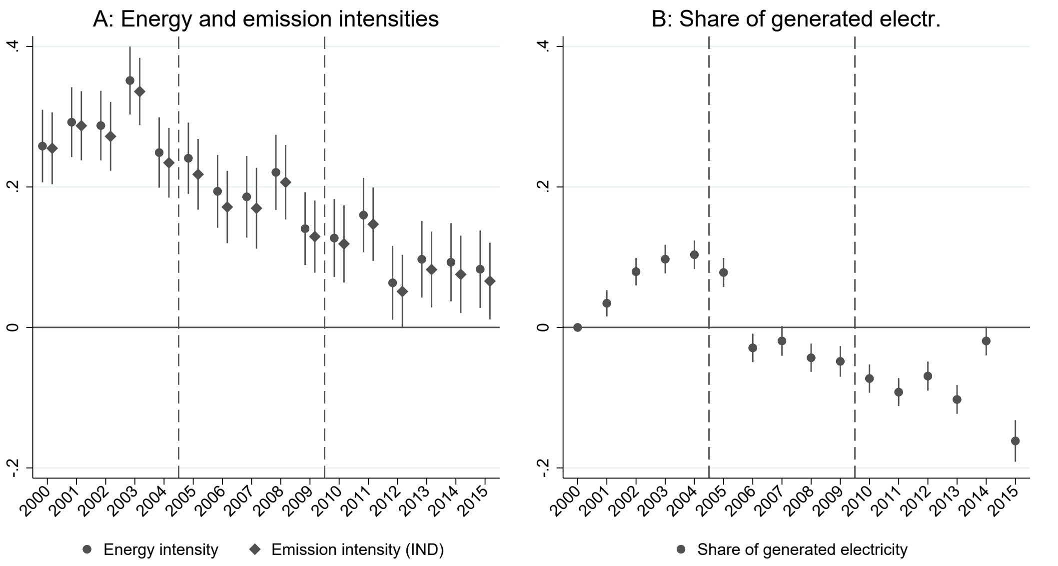
	Energy intensity (log MJ/VA) (1)	Emission intensity (log $kgCO_2e$/VA) (2)
Generator owner	0.196***	0.182***
	(0.007)	(0.007)
Observations	190,761	190,761
Adjusted R-squared	0.308	0.310
Firm controls	Yes	Yes
Firm FE	Yes	Yes
District-year FE	Yes	Yes
5-digit-sector-year FE	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1. Firm controls include total sales, capital stock, labor force size, and material input value.

sectors.

Results are presented in Table A3.4. Firms that use generators are about 22 percent more energy intensive compared to similar sized firms that do not use generators. Likewise, these firms are about 20 percent more emission intensive. These results may mask trends in generator use: The magnitude of the difference in energy and emission intensities between generator using and non-using firms depends on the intensity with which generators are used.

Figure A3.4 presents results of a regression with interactions between the generator ownership indicator year dummies as dependent variables, and energy and emission intensities as dependent variables. Clearly, the difference in intensities between generator-using and non-using firms becomes smaller over time. This is because the average share of self-generated electricity in total electricity use at the firm level decreases over time: In Panel B, we plot estimates of a regression of the subsample of generator-using firms, with the share of self-generated electricity as dependent variables, and year dummies as independent variables (and including firm control as well as district-year and 5-digit-sector-year fixed effects). After the diesel subsidy reform in 2005, the average share of self-generated electricity never reached pre-reform levels again. Two effects can explain why: First, diesel prices may discourage generator use, and hence they are used less often after the subsidy reform. Further, improvements in grid quality reduces the need for using generators during blackouts, as the latter become less frequent. Unfortunately, we cannot test the relative importance of both factors.



Notes: Vertical lines mark the years before the major diesel fuel (2005) and electricity tariff (2010) reforms.

Figure A3.4: Difference in energy and emission intensities between generator using and non-using firms, and average share of self-generated electricity in total electricity use, 2000–2015

C: Productivity Estimation

We estimate a value-added production function to recover revenue productivity estimates (TFPR). To avoid endogeneity issues due to unobserved productivity shocks, we employ the control function approach of Ackerberg et al. (2015), which solves functional dependence problems found in Olley and Pakes (1996) as well as Levinsohn and Petrin (2003). Consider the following Cobb-Douglas production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \epsilon_{it} \tag{A3.1}$$

where y_{it} is deflated value added of firm i in year t, k_{it} is the deflated value of capital, b_{it} the number of blue collar workers and w_{it} the number of white collar workers. ω_{it} is a productivity shock and ϵ_{it} an iid error term. All variables are expressed in logs.
We do not observe ω_{it}, but it is known by the firm and likely affects production as well as input choices. The control function approach models firm behaviour to infer productivity shocks from observables. Ackerberg et al. (2015) rely on following assumptions:

(1) The information set I_{it} of the firm includes current but not future productivity shocks and $E[\epsilon_{it}|I_{it}] = 0$.
(2) The distribution of productivity shocks follows a first-order Markov chain: $p(\omega_{it+1}|I_{it}) = p(\omega_{it+1}|\omega_{it})$.
(3) Accumulation of capital: $k_{it} = K(k_{it-1}, i_{it-1})$, with investment i chosen in $t-1$. Labour inputs are allowed to be chosen at t, $t-1$ or $t-b$, $0 < b < 1$.
(4) Intermediate input demand: $m_{it} = M(k_{it}, l_{it}, \omega_{it})$.
(5) $M(k_i, l_{it}, \omega_{it})$ is strictly increasing in ω_{it}: Productivity gains lead to higher intermediate input demand.

Inverting input-demand function gives $\omega_{it} = M^{-1}(k_{it}, l_{it}, m_{it})$. Plugging into equation (A3.1):

$$\begin{aligned} y_{it} &= \beta_0 + \beta_k k_{it} + \beta_l l_{it} + M^{-1}(k_{it}, l_{it}, m_{it}) + \epsilon_{it} \\ &= \Phi_t(k_{it}, l_{it}, m_{it}) + \epsilon_{it} \end{aligned} \tag{A3.2}$$

Equation A3.2 is estimated non-parametrically using GMM estimation and the respective moment condition. It produces an estimate of Φ_t, which is used in the second stage estimation. Using assumptions (1) and (2), ω_{it} is decomposed into the conditional expectation plus the innovation term of interest (ξ_{it}):

$$\omega_{it} = E[\omega_{it}|I_{it-1}] + \xi_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it} = g(\omega_{it-1}) + \xi_{it}$$

Substituting this expression into the production function then gives:

$$\begin{aligned} y_{it} =& \beta_0 + \beta_k k_{it} + \beta_l l_{it} \\ &+ g(\Phi_{t-1}(k_{it-1}, l_{it-1}, m_{it-1}) - \beta_0 - \beta_k k_{it-1} - \beta_l l_{it-1}) + \xi_{it} + \epsilon_{it} \end{aligned} \tag{A3.3}$$

which is again estimated using GMM with the respective moment condition. Predicting the residual after estimation produces the estimate of TFPR.

We estimate a translog production function relying on the Stata command *prodest* (Rovigatti and Mollisi, 2018) using 200 bootstrap repetitions, and split the sample according to three-digit industry identifiers. Values of value added, material and capital inputs are deflated by a nation-wide output/material/capital industry-price index. For 2006, the capital stock variable is missing. We infer the value from 2007 data, adding depreciation and subtracting sales.

D: Impact estimates, 2000 – 2008

Table A3.5: Results for generator use and capacity, as well as energy and emission intensities

	Generator ...		Intensity	
	... use	... capacity (*asinh* kW)	Energy	Emissions
	(1)	(2)	(3)	(4)
Past generator owner	-0.411***	-2.213***	-0.003	-0.012
× *log* diesel tariff	(0.017)	(0.110)	(0.031)	(0.031)
Observations	54,611	51,899	64,570	64,570
Adjusted R-squared	0.696	0.728	0.632	0.632
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes	Yes
5-digit-sector-year FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.6: Results for performance indicators

	log Sales	*log* VA	*log* VA/worker	*log* TFPR
	(1)	(2)	(3)	(4)
Past generator owner	-0.075***	-0.052**	-0.013	-0.002
× *log* diesel tariff	(0.022)	(0.024)	(0.021)	(0.004)
Observations	64,106	64,570	64,570	63,170
Adjusted R-squared	0.911	0.881	0.695	0.888
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes	Yes
5-digit-sector-year FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.7: Results for inputs: Capital, labor, and materials

	log No. of workers	*log* Capital	*log* Materials
	(1)	(2)	(3)
Past generator owner	-0.044***	0.026	-0.065**
$\times$ *log* diesel tariff	(0.012)	(0.025)	(0.027)
Observations	64,570	74,628	64,570
Adjusted R-squared	0.956	0.887	0.885
Firm controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes
5-digit-sector-year FE	Yes	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

E: Impact estimates, covariate balancing propensity score

Table A3.8: Results for generator use and capacity, as well as energy and emission intensities

	Generator ...		Intensity	
	... use	... capacity (*asinh* kW)	Energy	Emissions
	(1)	(2)	(3)	(4)
Past generator owner	-0.276***	-1.377***	-0.026	-0.033
× *log* diesel tariff	(0.010)	(0.061)	(0.029)	(0.029)
Observations	111,858	106,309	111,858	111,858
Adjusted R-squared	0.638	0.668	0.607	0.609
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes	Yes
5-digit-sector-year FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.9: Results for performance indicators

	log Sales	*log* VA	*log* VA/worker	*log* TFPR
	(1)	(2)	(3)	(4)
Past generator owner	-0.082***	-0.069***	-0.021	-0.003
× *log* diesel tariff	(0.021)	(0.022)	(0.019)	(0.003)
Observations	111,067	111,858	111,858	109,334
Adjusted R-squared	0.883	0.861	0.682	0.884
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes	Yes
5-digit-sector-year FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.10: Results for inputs: Capital, labor, and materials

	log No. of workers	*log* Capital	*log* Materials
	(1)	(2)	(3)
Past generator owner	-0.062***	-0.015	-0.084***
× *log* diesel tariff	(0.013)	(0.027)	(0.026)
Observations	111,858	128,590	111,858
Adjusted R-squared	0.911	0.836	0.851
Firm controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
District-year FE	Yes	Yes	Yes
5-digit-sector-year FE	Yes	Yes	Yes

Notes: Standard errors clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix to Chapter 4

Table A4.1: ENIGH-WIOD reduced matching and carbon intensities

			CI (kg/MXN)	
Item	WIOD code	WIOD description	CO_2	CO_2e
Electricity	17	Electricity, Gas and Water Supply	0.290	0.297
Motor Fuels	8	Coke, Refined Petroleum	0.217	0.222
Gas	8	Electricity, Gas and Water Supply	0.140	0.140
Public Transport	23	Inland Transport	0.029	0.031
Food	1	Agriculture	0.032	0.173
	3	Food processing	0.016	0.044
Other	4	Textiles	0.017	0.024
	5	Leather, Footwear	0.013	0.019
	6	Wood and Wood Products	0.018	0.047
	7	Pulp, Paper	0.019	0.020
	8	Chemicals and Products	0.014	0.022
	9	Rubber and Plastics	0.013	0.015
	10	Other Non-Metallic Mineral	0.056	0.100
	11	Basic Metals and Fabricated Metal	0.021	0.028
	12	Machinery	0.005	0.006
	13	Electrical and Optical Equipment	0.008	0.009
	14	Transport Equipment	0.008	0.010
	15	Manufacturing; Recycling	0.022	0.027
	16	Construction	0.018	0.023
	17	Sale Motor Vehicles and Fuel	0.017	0.019
	18	Wholesale and Commission Trade	0.008	0.010
	19	Retail Trade	0.012	0.014
	20	Hotels and Restaurants	0.025	0.026
	21	Water Transport	0.147	0.152
	22	Air Transport	0.013	0.075
	23	Other Transport	0.018	0.019
	24	Post and Telecommunications	0.008	0.009
	25	Financial Intermediation	0.004	0.005
	26	Real Estate Activities	0.004	0.004
	27	Renting of M&Eq and Other	0.009	0.010

			CI (kg/MXN)	
Item	WIOD code	WIOD description	CO_2	CO_2e
	28	Public Admin and Defence	0.015	0.016
	29	Education	0.012	0.012
	30	Health and Social Work	0.011	0.013
	31	Other Services	0.013	0.101

Appendix to Chapter 5

Appendix A: Tables

Table A5.1: ATT and CATT in rural and urban areas, *DiD* estimator

	Main fuel choice			Charcoal consumption			LPG expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Firewood	Charcoal	LPG	Average	Extensive	Intensive	Average	Extensive	Intensive
ATT	0.031**	-0.018	-0.013	0.028	-0.011	0.115	-0.039	-0.009	0.036
	(0.015)	(0.018)	(0.013)	(0.074)	(0.016)	(0.084)	(0.236)	(0.021)	(0.057)
N	10,384	10,384	10,384	10,384	10,384	3,534	10,384	10,384	1,818
Rural	0.052*	-0.041	-0.011	-0.127	-0.029	–	-0.026	-0.007	–
	(0.027)	(0.027)	(0.009)	(0.071)	(0.022)	–	(0.050)	(0.009)	–
N	4,720	4,720	4,720	4,720	4,720	–	4,720	4,720	–
Urban	0.033***	-0.031*	-0.002	0.164***	0.005	0.178*	-0.170	-0.019	0.072
	(0.011)	(0.016)	(0.018)	(0.048)	(0.013)	(0.086)	(0.468)	(0.038)	(0.056)
N	4,989	4,989	4,989	4,989	4,989	3,078	4,989	4,989	1,777

Notes: Standard errors clustered at the survey, treatment, ecological zone, and rural/urban levels. *** p<0.01, ** p<0.05, * p<0.1.

Table A5.2: Multinomial logit regression results, marginal effects

	(1)	(2)	(3)
Main cooking fuel:	Firewood	Charcoal	LPG
Log income per capita	-0.000	-0.001**	0.002***
	(0.000)	(0.001)	(0.000)
Log HH size	0.052***	-0.005	-0.048***
	(0.005)	(0.006)	(0.005)
Number of rooms	-0.007***	-0.025***	0.032***
	(0.002)	(0.003)	(0.002)
Dwelling self-owned	0.058***	-0.017**	-0.041***
	(0.006)	(0.007)	(0.006)
HH head: Male	0.000	-0.025***	0.025***
	(0.006)	(0.008)	(0.006)
HH head: Log age	0.035***	0.033***	-0.068***
	(0.008)	(0.011)	(0.008)
HH head: Log education	-0.019***	-0.007***	0.026***
	(0.002)	(0.003)	(0.002)
HH head: Agriculture	0.119***	-0.037***	-0.082***
	(0.006)	(0.010)	(0.009)
HH head: Unemployed	0.011	0.030***	-0.041***
	(0.009)	(0.011)	(0.009)
Main cook: Job weeks	-0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)
Main cook: Female	-0.012	-0.015	0.027***
	(0.009)	(0.011)	(0.008)
Main cook: Log education	-0.013***	-0.007***	0.020***
	(0.002)	(0.003)	(0.002)
Rural	0.200***	-0.139***	-0.061***
	(0.005)	(0.008)	(0.007)
Religion of head: Catholic	-0.019	-0.041**	0.060***
	(0.012)	(0.017)	(0.014)
Religion of head: Protestant	-0.039***	-0.025	0.064***
	(0.011)	(0.016)	(0.014)
Religion of head: Pentecostal/Charismatic	-0.027**	-0.018	0.045***
	(0.010)	(0.015)	(0.013)
Religion of head: Other Christian	0.001	-0.030*	0.029**
	(0.012)	(0.017)	(0.014)
Religion of head: Islam	-0.069***	0.029	0.040**
	(0.013)	(0.018)	(0.016)
Religion of head: Traditional	0.099***	-0.019	-0.080*
	(0.018)	(0.040)	(0.044)
Religion of head: Other	-0.172*	0.258**	-0.086
	(0.089)	(0.102)	(0.087)
Ethnicity of head: Ga-Dangme	0.040***	-0.024	-0.016
	(0.015)	(0.016)	(0.010)
Ethnicity of head: Ewe	0.033***	-0.018	-0.016*
	(0.012)	(0.013)	(0.009)
Ethnicity of head: Guan	0.076***	-0.057***	-0.020
	(0.016)	(0.020)	(0.016)
Ethnicity of head: Gurma	0.093***	-0.048*	-0.044*
	(0.018)	(0.025)	(0.023)
Ethnicity of head: Mole-Dagbani	0.076***	-0.042***	-0.034***
	(0.013)	(0.016)	(0.012)
Ethnicity of head: Grusi	0.095***	-0.105***	0.010
	(0.021)	(0.027)	(0.021)
Ethnicity of head: Mande	0.077***	-0.027	-0.050*
	(0.028)	(0.036)	(0.029)
Ethnicity of head: Other	0.013	-0.016	0.003
	(0.021)	(0.025)	(0.019)
Observations	15,126	15,126	15,126

Notes: HH = household. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Pseudo-R2 = 0.482. District dummies included but not reported. The base category of religion is "None". The base category of ethnicity is "Akan".

Appendix B: Cost-benefit analysis of the subsidy reform

This appendix presents our assumptions for the calculation of costs arising from fuel switching due to the subsidy reform. The calculations follow the methodology of Jeuland et al. (2018); we refer the interested reader to the supplementary material of that publication for further details. For all estimates, we present lower and upper bounds according to confidence intervals of our impact estimates (unless otherwise indicated below).

Health costs

The valuation of mortality and morbidity costs from increased fine particulate matter is based on parameter estimates of exposure response functions by Burnett et al. (2014) who relate concentrations of $PM_{2.5}$ to various respiratory (and related) diseases.[19] We first calculate the average $PM_{2.5}$ concentrations for households using firewood, charcoal or LPG. Then, we use the parameter estimates of Burnett et al. (2014)[20] to calculate the relative risk of mortality and morbidity for each of the four diseases included in their analysis. Using these relative risks and the shares of the population exposed to a specific level of air pollution, we calculate the population attributable fraction in order to assign the portion of disease risk that is attributable to $PM_{2.5}$ emissions from cooking. We compute the population shares under the assumption that households exclusively use either firewood, charcoal, or LPG, which implies that we ignore fuel stacking and will likely overestimate impacts on mortality and morbidity. Changes in the population attributable risk, which result from shifts in households' cooking fuel choices, are then multiplied by the average household size of urban and rural households (from the GLSS6) as well as the mortality and incidence (morbidity) rates. Increases in morbidity are converted to a cost measure using the cost-of-illness, whereas increases in mortality are valued according to the value of a statistical life. These household-level costs are then annualized and multiplied by the number of urban and rural households, respectively. For all parameter assumptions we use the medium values reported in Jeuland et al. (2018) and assume that households use traditional stoves for both firewood and charcoal consumption, since only few in Ghana report using ICS. Lower- and upper-bound estimates of fuel switching are derived from the confidence intervals of our impact estimates on main fuel choice, where rural estimates are set to zero for the lower bound of the firewood estimate and for the upper bounds of the charcoal and LPG estimates.

[19] Health costs only include costs of increased incidence of acute lower respiratory infections, chronic obstructive pulmonary disease, lung cancer, and ischemic heart diseases due to increases in the concentration of fine particulate matter ($PM_{2.5}$).

[20] Parameter estimates downloadable at: `http://ghdx.healthdata.org/sites/default/files/record-attached-files/IHME_CRCurve_parameters.csv`.

Emissions

Cooking with biomass not only emits CO_2 but also other GHGs such as carbon monoxide, methane, other nonmethane hydrocarbons, and black carbon. We associate average increases or decreases in cooking fuel (in kg) with $kgCO_2e$ emissions of each pollutant, using fuel-specific emission factors and 100-year global warming potentials of each pollutant. Further, we adjust CO_2 emissions by the share of biomass harvest that is unsustainable based on Bailis et al. (2015), which is 11 percent for Ghana. We do not consider emissions from transportation. To calculate changes in emissions, we need to compute changes in fuel quantities using various assumptions. For urban areas, we assume that those 1.1-5.5 percent of households switching to mainly using firewood increase firewood consumption according to pre-reform differences in consumption of charcoal between subsets of households mainly using charcoal, and households mainly using firewood. The subsets of households are determined as follows: We include those households mainly using firewood with a probability of mainly using charcoal above 50 percent (based on estimated propensity scores of a multinomial logit model, see Table A5.2). The second subset consists of households that mainly use charcoal with a high predicted probability of mainly using firewood. Using the charcoal quantity changes, assuming that cooking energy is constant, and using parameters on the net calorific value of firewood and charcoal (19.0 MJ/kg and 29.8 MJ/kg respectively, based on water boiling tests, from Garland et al., 2015), we can now compute the changes in firewood consumption (in kg). Total charcoal consumption differences are computed according to our estimates and pre-reform average consumption levels. Total LPG quantity changes are computed as residual using the net calorific values of each fuel, assuming that the net calorific value of cooking remains constant. For rural areas, we estimate changes in total charcoal consumption according to our estimates and pre-reform consumption levels. Changes in firewood consumption are computed as residual using the net calorific values of both fuels under the assumption of constant energy consumption and negligible changes in LPG use.

Time costs

GLSS6 provides information on time spent cooking and collecting firewood. In urban households that mainly use firewood for cooking, members spend about 45 hours in total on both activities, of which around 10 hours are spent collecting wood. Urban households that mainly use charcoal cook for around 27 hours per month, compared to 23 hours for households using mainly LPG. Rural households that mainly use firewood spend in total 54 hours cooking and collecting firewood per month, while those that mainly use charcoal (LPG) spend around 27 (26) hours per month cooking. These figures provide the basis for assessment of additional time costs, where we value each working day (8 hours) by the minimum wage (around USD 2.7 in 2013). The lower- and upper-bound estimates are again derived from confidence intervals. For substitution of charcoal for LPG at the intensive margin, we assume that cooking time increases according to the expanded use of charcoal. Costs are again aggregated over all urban and rural households in Ghana. Note that these costs exclude the difficult-to-quantify long-term time costs for women and children due to firewood collection and increased cooking time, which can be substantial in terms of labor market participation or education (Biswas and Das, 2022).

Fuel costs

Pre-reform expenditure levels form the basis of our estimates of fuel cost changes. Households switching to mainly using firewood increase related expenditure according to pre-reform differences therein between households mainly using charcoal and households mainly using firewood. Note that firewood expenditures are very low because only 9 percent of households that mainly use firewood purchase it. We assume that the price of (purchased) firewood increases by 20 percent due to increased transportation costs (see Table 5.4). We tally average pre-reform charcoal expenditure according to both the increase in average consumption and the average price increase of about 20 percent. We assume no expenditure increases for LPG for the lower-bound estimate, and a 30 percent increase in LPG expenditure for the upper-bound one (in line with our assumptions for GHG emissions outlined above). For transport fuel costs, we do not consider potential fuel switching behavior. We compute indirect welfare effects based on figures provided in Cooke et al. (2016), who estimate that indirect welfare effects of the reform make up about 35 percent of the total welfare effect, on average.

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Autorenbeiträge

Chapter 2: How vulnerable are small firms to energy price increases? Evidence from Mexico

- Ana Karen Negrete, Jann Lay, and Hannes Greve conceptualized the study
- Ana Karen Negrete and Hannes Greve conducted the literature review
- Ana Karen Negrete prepared the data for analysis
- Hannes Greve and Jann Lay developed the analytical strategy
- Hannes Greve analyzed the data
- Ana Karen Negrete contributed to analyzing the data
- Ana Karen Negrete, Jann Lay, and Hannes Greve interpreted the results
- Ana Karen Negrete, Jann Lay, and Hannes Greve wrote the manuscript

Chapter 3: Energy prices, generators, and the performance of manufacturing firms: Evidence from Indonesia

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- Hannes Greve analyzed the data
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Chapter 4: Household welfare and CO_2 emission impacts of energy and carbon taxes in Mexico

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Chapter 5: ”Stepping down the ladder”: The impacts of fossil fuel subsidy removal in a developing country

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- Hannes Greve developed the analytical strategy
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- Hannes Greve analyzed the data
- Jann Lay and Hannes Greve interpreted the results
- Jann Lay and Hannes Greve wrote the manuscript