Methodological appendix:

# A transição da indústria brasileira para veículos elétricos e seus efeitos em emprego e renda

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## List of acronyms

BEV – Battery electric vehicle

CNG – Compressed natural gas

EV – Electric vehicle

FCEV – Fuel cell electric vehicle (powered by hydrogen)

GVW – Gross vehicle weight

HDV – Heavy-duty vehicle

HVO – Hydrotreated vegetable oil, a drop-in biofuel for diesel-cycle engines

ICEV – Internal combustion engine vehicle

ICE biodiesel – Diesel-cycle internal combustion engine vehicle using 100% biodiesel (HVO)

ICE ethanol – Otto-cycle internal combustion engine vehicle using 100% ethanol

ICE diesel – Diesel-cycle internal combustion engine vehicle using 100% national blend of diesel B (88% fossil diesel + 12% biodiesel)

ICE gasoline – Otto-cycle internal combustion engine vehicle using 100% national blend of gasoline C (72% fossil gasoline + 27% ethanol)

ILUC – Indirect land use change

LDV – Light-duty vehicle

LNG – Liquified natural gas

## THE SYNTHETIC EV PRODUCTION INDUSTRY

This section details the data employed to develop the synthetic EV production industry presented in Section 3 of the main report (*A Cadeia Productiva de Veículos Elétricos)*.

Table A1 presents the cost of EV components as a percentage of total vehicle production costs (see Figure 1 of the main report). The table lists the segment and model considered as well as the source for the data. The mean values used to build the synthetic EV industry are weighted by the vehicle sales in each segment in Brazil.

### TABLE A1. COMPONENT COST AS A PERCENTAGE OF TOTAL EV PRODUCTION COST

| Country/region | India | | Europe | | | | | United States | | | | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Segment/model | Bus, 12 m | Truck, 16 t | Class 4-5 rigid truck | Class 6-7 rigid truck | Class 8 rigid truck | Tractor-trailer, short-haul | Tractor-trailer, long-haul | Car | VW ID.4 (car) | Van | Pick-up | |
| Source | EY-Parthenon (2023) | | Xie et al. (2023) | | | | | Slowik et al. (2022) | FEV Consulting (2023) | Mulholland (2022) | | |
| **Powertrain** | **39%** | **56%** | **48%** | **50%** | **49%** | **52%** | **60%** | **49%** | **42%** | **30%** | **33%** | **44%** |
| Battery | 28% | 46% | 25% | 29% | 34% | 37% | 51% | 37% | 31% | 22% | 23% | 32% |
| E-drive & other powertrain | 11% | 10% | 23% | 21% | 15% | 15% | 8% | 12% | 11% | 8% | 11% | 11% |
| **Direct non-powertrain** | **25%** | **9%** | **22%** | **19%** | **21%** | **18%** | **11%** | **23%** | **30%** | **42%** | **39%** | **28%** |
| Drivetrain | 7% | 5% | 8% | 7% | 8% | 7% | 4% | 6% | 8% | 11% | 10% | 8% |
| Suspension | 2% | 0% | 1% | 1% | 1% | 1% | 1% | 1% | 2% | 3% | 2% | 2% |
| Steering | 2% | 2% | 2% | 2% | 2% | 2% | 1% | 1% | 1% | 1% | 1% | 1% |
| Axle | 2% | 1% | 2% | 2% | 2% | 2% | 1% | 0% | 0% | 0% | 0% | 0% |
| Tires and wheels | 1% | 1% | 1% | 1% | 1% | 1% | 1% | 2% | 2% | 3% | 3% | 2% |
| Braking | 1% | 1% | 1% | 1% | 1% | 1% | 1% | 2% | 2% | 3% | 3% | 2% |
| Driveshaft | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 1% | 1% | 1% | 1% | 1% |
| Body and chassis | 11% | 3% | 7% | 7% | 8% | 6% | 4% | 11% | 15% | 21% | 19% | 14% |
| Accessories and auxiliaries | 7% | 0% | 7% | 5% | 5% | 5% | 3% | 5% | 7% | 10% | 9% | 7% |
| **Indirect costs** | **36%** | **35%** | **30%** | **30%** | **30%** | **30%** | **29%** | **28%** | **28%** | **28%** | **28%** | **28%** |
| Total | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% |

We then associated the different components listed above to specific industries. Starting from the 6-digit North American Industry Classification System (NAICS), we allocated each EV component into one of 1,102 possible industries. We then used industry code crosswalks to allocate the components into the Standard Industrial Classification (SIC), then into Brazil's *Classificação Nacional de Atividade Econômicas* (CNAE 2.0), and finally into the 67 industries of the *Sistema de Contas Nacionais* (SCN) listed in Brazil's input-output tables.

The correspondence between components and industries is presented in Table A2, while the allocation of costs into industries is illustrated in Figure 2 of the main report.

## TABLE A2. CORRESPONDENCE BETWEEN EV COMPONENTS AND INDUSTRY CODES

<table>
<tr><th colspan="2">Component</th><th>NAICS 2022 6d</th><th>SIC</th><th>CNAE 2.0</th><th>SCN</th></tr>
<tr><td rowspan="3">Battery</td><td>Battery pack</td><td rowspan="3">Battery Manufacturing (335910)</td><td rowspan="3">Storage batteries (3691)</td><td rowspan="3">Manufacturing of electrical machinery and equipment (2700)</td><td rowspan="7">Manufacturing of electrical equipment (2700)</td></tr>
<tr><td>Battery management system</td></tr>
<tr><td>Battery thermal management</td></tr>
<tr><td rowspan="4">E-drive</td><td>Motor</td><td>Motor and Generator Manufacturing (335312)</td><td>Motors and generators (3621)</td><td>Manufacturing of generators, transformers, and electric motors (27.10-4)</td></tr>
<tr><td rowspan="3">Control unit/inverter, DC converter, HV cables</td><td>Switchgear and Switchboard Apparatus Manufacturing (335313)</td><td>Switchgear and switchbox apparatus (3613)</td><td>Manufacturing of devices and equipment for distribution and control of electric power (27.31-7)</td></tr>
<tr><td>Other Communication and Energy Wire Manufacturing (335929)</td><td rowspan="2">Drawing and insulating nonferrous wire (3357)</td><td>Manufacturing of electrical material for installations in consumer circuits (27.32-5)</td></tr>
<tr><td>Current-Carrying Wiring Device Manufacturing (335931)</td><td>Manufacturing of insulated electric wires, cables, and conductors (27.33-3)</td></tr>
<tr><td rowspan="7">Drivetrain</td><td>Suspension</td><td>Ornamental and Architectural Metal Work Manufacturing (332323)</td><td>Architectural metalwork (3446)</td><td rowspan="3">Manufacturing of parts and accessories for the steering and suspension system of motor vehicles (29.44-1)</td><td rowspan="3">Manufacturing of parts and accessories for motor vehicles (2992)</td></tr>
<tr><td>Steering</td><td>Motor Vehicle Steering and Suspension Components (except Spring) Manufacturing (336330)</td><td>Motor vehicle parts and accessories (3714)</td></tr>
<tr><td>Axle</td><td>Motor Vehicle Transmission and Power Train Parts Manufacturing (336350)</td><td>Motor vehicle parts and accessories (3714)</td></tr>
<tr><td rowspan="2">Tires and wheels</td><td>Motor Vehicle Body Manufacturing (326211)</td><td>Tires and inner tubers (3011)</td><td>Manufacturing of tires and inner tubes (22.11-1)</td><td>Manufacturing of rubber and plastic products (2200)</td></tr>
<tr><td>Iron and Steel Mills and Ferroalloy Manufacturing (331110)</td><td>Steel works, blast furnaces and rolling and finishing mills (3312)</td><td>Manufacturing of other parts and accessories for motor vehicles not specified elsewhere (29.49-2/99)</td><td rowspan="3">Manufacturing of parts and accessories for motor vehicles (2992)</td></tr>
<tr><td>Braking</td><td>Motor Vehicle Brake System Manufacturing (3363400</td><td>Motor vehicle parts and accessories (3714)</td><td>Manufacturing of parts and accessories for the brake system of motor vehicles (29.43-3)</td></tr>
<tr><td>Driveshaft</td><td>Motor Vehicle Transmission and Power Train Parts Manufacturing (336350)</td><td>Motor vehicle parts and accessories (3714)</td><td>Manufacturing of parts and accessories for the gear and transmission systems of motor vehicles (29.42-5)</td></tr>
<tr><td rowspan="2">Body and chassis</td><td>Body/cabin</td><td>Motor Vehicle Metal Stamping (336370)</td><td>Automotive stamping (3465)</td><td>Manufacturing of cabins, bodies, and trailers for motor vehicles (29.30-1)</td><td rowspan="2">Manufacturing of automobiles, trucks, and buses, except parts (2991)</td></tr>
<tr><td>Ladder frame chassis</td><td>Automobile and Light Duty Motor Vehicle Manufacturing (336110)</td><td>Motor vehicles and passenger car bodies (3711)</td><td>Manufacturing of trucks and buses (29.20-4)</td></tr>
</table>

To build the synthetic EV industry, once the components were associated with one of the 67 industries that supply intermediate inputs to EV production, we differentiated between core and non-core parts and components. Core parts and components include batteries, components of the electric powertrain (such as electric motors), body, chassis, and traditional drivetrain parts like the suspension, axle, braking and steering systems, driveshafts, tires, and wheels. These components correspond to intermediate inputs sourced from the EV industry itself and the manufacturing of electrical equipment (2700) and manufacturing of auto parts (2992) industries.

For non-core parts, we assumed that the production of one ICE vehicle and one EV require the same intermediate inputs. In other words, we assumed that ICEVs and EVs require the same wheels and tires, metal for the body, plastics, and services. This approach is analogous to the one adopted by Tamba et al. (2022, p. 3). We acknowledge that there are differences in these non-core components between ICEVs and EVs. For instance, EVs tend to have more technology on average, such that their demand for microchips, screens, and software is likely higher than for the average ICEV. However, since most of the production costs are concentrated in core industries, we expect this simplification to have limited impact on the results.

To determine the demand for core components, we relied on the costs of non-core components and the relative (%) costs that each component represents in an EV (presented in Table A1, above). For instance, if we know that tires and wheels represent 7% of the average EV production cost, corresponding to R$ 1,000,000, and the battery represents 32% of the average EV costs, the cost of batteries will be $\frac{0.32}{0.07}.\,1{,}000{,}000 = \text{R\$}\ 4{,}571{,}428$. We repeat this procedure to obtain the intermediate demand for all core components and for the value added, the sum of profits and wages, of the EV industry (see explanation of Table A4).

We then allocated demand for intermediate inputs into domestic and foreign industries. For all industries except battery manufacturing, we multiplied the intermediate demand by the share of domestic and foreign inputs in the domestic ICEV production industry observed in the national input-output matrix. The production cost of batteries, meanwhile, was allocated to the electrical equipment manufacturing industry (2700) as determined by the scenarios plotted in panel (3) of Box.1 of the main report.

To calculate the technical coefficients of the synthetic EV industry, we divided the value of intermediate inputs demand from an industry $i$ ($Z_i$) by the gross production value $Y = \frac{\sum_{i=1}^{68} Z_i + \sum_{i=1}^{68} M_i}{1 - p_{VA}}$, where $M_i$ are the intermediate inputs demanded from foreign industries and $p_{VA}$ is the value added as percentage of gross production value. Applying these procedures, we obtained the technical coefficients for the synthetic EV industry's demand for domestic intermediate inputs, shown in Table A3. The procedure for the synthetic EV industry as a supplier is explained in below.

### TABLE A3. DOMESTIC TECHNICAL COEFFICIENTS FOR THE SYNTHETIC EV PRODUCTION INDUSTRY

| SCN | Industry name | A Domestic | A Imports |
|---|---|---|---|
| | Fabricação de Veículos Elétricos | 0.02897 | 0.00756 |
| 0191 | Agricultura, inclusive o apoio à agricultura e a pós-colheita | 0.00000 | 0.00000 |

| SCN | Industry name | A Domestic | A Imports |
|---|---|---|---|
| 2992 | Fabricação de peças e acessórios para veículos automotores | 0.03817 | 0.01965 |
| 3000 | Fabricação de outros equipamentos de transporte, exceto veículos automotores | 0.00026 | 0.00008 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 0192 | Pecuária, inclusive o apoio à pecuária | 0.00001 | 0.00000 | 3180 | Fabricação de móveis e de produtos de indústrias diversas | 0.00125 | 0.00038 |
| 0280 | Produção florestal; pesca e aquicultura | 0.00000 | 0.00000 | 3300 | Manutenção, reparação e instalação de máquinas e equipamentos | 0.00098 | 0.00027 |
| 0580 | Extração de carvão mineral e de minerais não metálicos | 0.00008 | 0.00001 | 3500 | Energia elétrica, gás natural e outras utilidades | 0.00277 | 0.00000 |
| 0680 | Extração de petróleo e gás, inclusive as atividades de apoio | 0.00011 | 0.00018 | 3680 | Água, esgoto e gestão de resíduos | 0.00059 | 0.00000 |
| 0791 | Extração de minério de ferro, inclusive beneficiamentos e a aglomeração | 0.00000 | 0.00000 | 4180 | Construção | 0.00100 | 0.00023 |
| 0792 | Extração de minerais metálicos não ferrosos, inclusive beneficiamentos | 0.00004 | 0.00001 | 4500 | Comércio por atacado e varejo | 0.08282 | 0.00262 |
| 1091 | Abate e produtos de carne, inclusive os produtos do laticínio e da pesca | 0.00011 | 0.00000 | 4900 | Transporte terrestre | 0.02373 | 0.00046 |
| 1092 | Fabricação e refino de açúcar | 0.00004 | 0.00000 | 5000 | Transporte aquaviário | 0.00165 | 0.00003 |
| 1093 | Outros produtos alimentares | 0.00051 | 0.00004 | 5100 | Transporte aéreo | 0.00101 | 0.00017 |
| 1100 | Fabricação de bebidas | 0.00011 | 0.00001 | 5280 | Armazenamento, atividades auxiliares dos transportes e correio | 0.01652 | 0.00010 |
| 1200 | Fabricação de produtos do fumo | 0.00001 | 0.00000 | 5500 | Alojamento | 0.00045 | 0.00043 |
| 1300 | Fabricação de produtos têxteis | 0.00057 | 0.00020 | 5600 | Alimentação | 0.00168 | 0.00032 |
| 1400 | Confecção de artefatos do vestuário e acessórios | 0.00003 | 0.00000 | 5800 | Edição e edição integrada à impressão | 0.00001 | 0.00000 |
| 1500 | Fabricação de calçados e de artefatos de couro | 0.00009 | 0.00003 | 5980 | Atividades de televisão, rádio, cinema e gravação/edição de som e imagem | 0.00001 | 0.00000 |
| 1600 | Fabricação de produtos da madeira | 0.00078 | 0.00001 | 6100 | Telecomunicações | 0.00531 | 0.00013 |
| 1700 | Fabricação de celulose, papel e produtos de papel | 0.00151 | 0.00016 | 6280 | Desenvolvimento de sistemas e outros serviços de informação | 0.00434 | 0.00025 |
| 1800 | Impressão e reprodução de gravações | 0.00013 | 0.00001 | 6480 | Intermediação financeira, seguros e previdência complementar | 0.01393 | 0.00117 |
| 1991 | Refino de petróleo e coquerias | 0.00467 | 0.00020 | 6800 | Atividades imobiliárias | 0.00044 | 0.00001 |
| 1992 | Fabricação de biocombustíveis | 0.00009 | 0.00001 | 6980 | Atividades jurídicas, contábeis, consultoria e sedes de empresas | 0.00999 | 0.00035 |
| 2091 | Fabricação de químicos orgânicos e inorgânicos, resinas e elastômeros | 0.00069 | 0.00034 | 7180 | Serviços de arquitetura, engenharia, testes/análises técnicas e P & D | 0.00536 | 0.00181 |
| 2092 | Fabricação de defensivos, desinfestantes, tintas e químicos diversos | 0.00229 | 0.00053 | 7380 | Outras atividades profissionais, científicas e técnicas | 0.01800 | 0.00089 |
| 2093 | Fabricação de produtos de limpeza, cosméticos/perfumaria e higiene pessoal | 0.00020 | 0.00003 | 7700 | Aluguéis não imobiliários e gestão de ativos de propriedade intelectual | 0.00156 | 0.00819 |
| 2100 | Fabricação de produtos farmoquímicos e farmacêuticos | 0.00018 | 0.00006 | 7880 | Outras atividades administrativas e serviços complementares | 0.00676 | 0.00025 |
| 2200 | Fabricação de produtos de borracha e de material plástico | 0.03657 | 0.01296 | 8000 | Atividades de vigilância, segurança e investigação | 0.00255 | 0.00000 |
| 2300 | Fabricação de produtos de minerais não metálicos | 0.00939 | 0.00158 | 8400 | Administração pública, defesa e seguridade social | 0.00266 | 0.00018 |
| 2491 | Produção de ferro gusa/ferroligas, siderurgia e tubos de aço sem costura | 0.02418 | 0.00660 | 8591 | Educação pública | 0.00029 | 0.00000 |
| 2492 | Metalurgia de metais não ferosos e a fundição de metais | 0.00331 | 0.00129 | 8592 | Educação privada | 0.00059 | 0.00001 |
| 2500 | Fabricação de produtos de metal, exceto máquinas e equipamentos | 0.01645 | 0.00382 | 8691 | Saúde pública | 0.00003 | 0.00000 |
| 2600 | Fabricação de equipamentos de informática, produtos eletrônicos e ópticos | 0.00125 | 0.00194 | 8692 | Saúde privada | 0.00000 | 0.00000 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2700 | Fabricação de máquinas e equipamentos elétricos | 0.14599 | 0.29309 | 9080 | Atividades artísticas, criativas e de espetáculos | 0.00054 | 0.00003 |
| 2800 | Fabricação de máquinas e equipamentos mecânicos | 0.00554 | 0.00355 | 9480 | Organizações associativas e outros serviços pessoais | 0.00132 | 0.00000 |
| 2991 | Fabricação de automóveis, caminhões e ônibus, exceto peças | - | - | 9700 | Serviços domésticos | - | - |

To obtain the technical coefficients in Table A3, it is necessary to determine the value added in the EV industry. To do so we relied on the sources presented in Table A4, which provide the ratios between value added in traditional ICEV manufacturing and EV manufacturing. On average, the value added in EV manufacturing is 84% of that in ICEV manufacturing.[1]

The value added for Brazil's synthetic EV production industry was obtained by multiplying the average ratio in the table by the actual value added observed for ICEV production in Brazil, which was 11.6% in our baseline year of 2019. Thus, the value added for the EV production industry was set at 9.76% $(84.1\% * 11.6\% = 9.76\%)$.

### TABLE A4. VALUE ADDED OF THE SYNTHETIC EV PRODUCTION INDUSTRY (% OF TOTAL COST)

| Reference | V.A. ICEVs | V.A. Evs | EVs/ICEVs |
|---|---:|---:|---:|
| Tamba et al. (2022) | 16.7% | 10.4% | 62.3% |
| FEV Consulting (2023) | 16.7% | 17.7% | 105.9% |
| **Mean** | **16.7%** | **14.1%** | **84.1%** |

As mentioned above, the demand for batteries, domestic and imported, was determined by different scenarios. However, we assumed the minimum domestic content is equivalent to the cost of pack assembly, battery management systems (BMS), and battery thermal management (BTM), which represent, on average, 21% of total vehicle production costs. In the other scenarios, this domestic content is assumed to increase linearly, at different rates, until 2050 as shown in Box 1 of the main report.

### TABLE A5. COMPONENT COST OF LITHIUM-ION BATTERY PACKS

| References | Cells | Pack assembly | BMS + BTM |
|---|---:|---:|---:|
| Ricardo plc. (2021) | 79% | 18% | 4% |
| FEV Consulting (2023) | 82% | 16% | 1% |
| UBS (2017) | 76% | 22% | 2% |
| **Mean** | **79%** | **19%** | **2%** |

[1] The smaller value added percentage does not necessarily imply a reduction of gross value added for EVs, as the gross production value, for a similar amount of vehicles produced, is higher than for ICEV production.

## Scenario development

Our scenarios apply alternative hypotheses on the evolution of vehicles sales by segment and powertrain to determine total sales of vehicles and fuel and electricity demands. The methodologies that underlie the simulation of new vehicles sales and fleet demand for fuels and electricity are presented in the Roadmap model documentation (ICCT, 2022). Examples of previous applications of the Roadmap model to determine fleet projections, energy demand, and emissions at global and national levels include Sen et al. (2023), Sen and Miller (2022), and Jin et al. (2021).

### The assumptions on vehicle sales by segment and powertrain used in our study (see Figure 3 and Box 1 of the main report) are detailed in Table A6 for the Baseline scenario (*cenário Base*) and in

Table A7 for the Electrification scenario (*cenário Eletrificação).* The objective of this study is to compare the impact of EV and ICEV production on economic and employment indicators, rather than providing an accurate projection of future vehicle sales. This is why the scenarios focus exclusively on the production of electric and (fossil fuel- and biofuel-powered) ICE vehicles, and excludes full hybrids, plug-in hybrids, CNG ICEVs, LNG ICEVs, and FCEVs.

### Table A6. Baseline scenario: projected sales by segment and power train

| Segment | Powertrain | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|
| Bus | BEV | 0% | 4% | 15% | 28% | 45% | 57% | 67% |
| | ICE Biodiesel | 0% | 0% | 3% | 5% | 8% | 10% | 13% |
| | ICE Diesel | 72% | 70% | 58% | 46% | 32% | 20% | 10% |
| | ICE Ethanol | 10% | 10% | 11% | 10% | 8% | 6% | 5% |
| | ICE Gasoline | 18% | 16% | 13% | 10% | 7% | 5% | 4% |
| Heavy-duty trucks | BEV | 0% | 1% | 1% | 1% | 1% | 3% | 7% |
| | ICE Biodiesel | 0% | 0% | 3% | 15% | 27% | 39% | 52% |
| | ICE Diesel | 100% | 99% | 96% | 84% | 71% | 57% | 42% |
| Medium-duty trucks | BEV | 0% | 1% | 2% | 3% | 6% | 10% | 14% |
| | ICE Biodiesel | 0% | 0% | 3% | 14% | 25% | 36% | 47% |
| | ICE Diesel | 100% | 99% | 95% | 83% | 69% | 54% | 38% |
| Light commercial vehicles | BEV | 0% | 1% | 2% | 5% | 12% | 22% | 30% |
| | ICE Biodiesel | 0% | 0% | 3% | 7% | 11% | 15% | 19% |
| | ICE Diesel | 49% | 49% | 46% | 42% | 38% | 34% | 30% |
| | ICE Ethanol | 18% | 20% | 22% | 22% | 20% | 16% | 11% |
| | ICE Gasoline | 33% | 30% | 26% | 23% | 19% | 13% | 9% |
| Passenger cars | BEV | 0% | 1% | 2% | 3% | 4% | 5% | 8% |
| | ICE Ethanol | 36% | 39% | 45% | 47% | 50% | 51% | 51% |
| | ICE Gasoline | 64% | 60% | 53% | 50% | 46% | 44% | 41% |

### TABLE A7. ELECTRIFICATION SCENARIO: PROJECTED SALES BY SEGMENT AND POWER TRAIN

| Segment | Powertrain | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|
| Bus | BEV | 0% | 4% | 20% | 50% | 70% | 90% | 100% |
| | ICE Biodiesel | 0% | 0% | 3% | 7% | 11% | 4% | 0% |
| | ICE Diesel | 72% | 69% | 55% | 29% | 10% | 3% | 0% |
| | ICE Ethanol | 10% | 11% | 10% | 7% | 4% | 2% | 0% |
| | ICE Gasoline | 18% | 16% | 12% | 7% | 4% | 1% | 0% |
| Heavy-duty trucks | BEV | 0% | 1% | 3% | 5% | 15% | 25% | 40% |
| | ICE Biodiesel | 0% | 0% | 3% | 11% | 18% | 26% | 33% |
| | ICE Diesel | 100% | 99% | 94% | 84% | 67% | 49% | 27% |
| Medium-duty trucks | BEV | 0% | 3% | 15% | 25% | 55% | 70% | 90% |
| | ICE Biodiesel | 0% | 0% | 3% | 4% | 4% | 5% | 6% |
| | ICE Diesel | 100% | 97% | 82% | 71% | 41% | 25% | 4% |
| Light commercial vehicles | BEV | 0% | 3% | 10% | 20% | 50% | 60% | 75% |
| | ICE Biodiesel | 0% | 0% | 3% | 8% | 13% | 11% | 7% |
| | ICE Diesel | 49% | 47% | 41% | 31% | 12% | 9% | 5% |
| | ICE Ethanol | 18% | 19% | 21% | 20% | 13% | 11% | 7% |
| | ICE Gasoline | 33% | 30% | 25% | 21% | 12% | 9% | 6% |
| Passenger cars | BEV | 0% | 3% | 6% | 15% | 40% | 50% | 70% |
| | ICE Ethanol | 36% | 38% | 43% | 41% | 31% | 27% | 17% |
| | ICE Gasoline | 64% | 59% | 51% | 44% | 29% | 23% | 13% |

## INPUT-OUTPUT MODEL FOR ELECTRIC MOBILITY: THE BRAZILIAN CASE

This section presents a benchmark method to estimate the impact of changes in electric mobility on output and employment. It adapts the Brazilian input-output matrix for 2019 (Alves-Passoni & Freitas, 2020) by including a synthetic sector that represents the EV sector following the method conceived in Kim et al. (2017; 2019) and employed in Marques et al. (2023). It simulates scenarios for changes in EV demand and production for the 2019–2050 period using the Roadmap model's projections (ICCT, 2022). It also considers sensitivity analyses regarding changes in the domestic component of battery production and in exports.

The following boxes detail the simulation code develop in R.

```
#Loading necessary packages
library(dplyr)
library(readxl)
library(data.table)
library(ggplot2)
library(stringr)
library(estimatr)
library(ggthemes)
library(stargazer)
library(texreg)
library(modelsummary)
library(tidyr)
library(ggplot2)
library(tidyverse)
library(openxlsx)
library(flextable)
library(gridExtra)
library(knitr)
library(scales)
library(ggrepel)
library(tibble)
```

### LOADING DATA

We began by importing the original matrices allowing for the calculation of the input-output model as the employed method implies their manipulation and adaptation.

These matrices are: **"s"** - supply matrix (activity x sector), **"u"** - domestic use matrix (activity x sector), **"Adom"** - domestic use matrix (sector x sector), **"Aimp"** - imported use matrix (sector x sector), **"Y"** - output (sector), **"L"** - occupations (sector), **"VA"** - value added (sector), **"W"** - employee's compensation (sector), **"fd_sector"** - final demand from domestic use matrix (sector).

```
s <- as.matrix(read_excel("C://Users/…//MIP2019_67setores.xlsx", sheet
= "Recursos", range = "c5:cb133", col_names = T))
u <- as.matrix(read_excel("C://Users//…//MIP2019_67setores.xlsx", sheet
 = "Usos Nacional", range = "c5:bz133", col_names = T))
Adom <- as.matrix(read_excel("C://Users//…//MIP2019_67setores.xlsx", sh
```

```
eet = "Usos Nacional (Atividade DUsos)", range = "c6:bq72", col_names =
 F))
Aimp <- as.matrix(read_excel("C://Users//…//MIP2019_67setores.xlsx", sh
eet = "Usos Import (Atividade DUm)", range = "c6:bq72", col_names = F))
Y <- as.matrix(read_excel("C://Users//…//MIP2019_67setores.xlsx", sheet
 = "Usos", range = "c154:bq154", col_names = F))
L <- as.matrix(read_excel("C://Users//…//MIP2019_67setores.xlsx", sheet
 = "Usos", range = "c155:bq155", col_names = F))
VA <- as.matrix(read_excel("C://Users//…//MIP2019_67setores.xlsx", shee
t = "Usos", range = "c142:bq142", col_names = F))
W <- as.matrix(read_excel("C://Users//…//MIP2019_67setores.xlsx", sheet
 = "Usos", range = "c143:bq143", col_names = F))
fd_sector <- as.matrix(read_excel("C://Users//…//MIP2019_67setores.xlsx
", sheet = "Usos Nacional (Atividade DUsos)", range = "by6:by72", col_n
ames = F))

#labels for activities and sectors:
label_prod <- as.matrix(read_excel("C://Users//pedro//Downloads//ev//MI
P2019_67setores.xlsx", sheet = "Recursos", range = "b5:b131", col_names
 = T))
label_sector <- as.matrix(read_excel("C://Users//pedro//Downloads//ev//
//MIP2019_67setores.xlsx", sheet = "Usos Nacional (Atividade DUsos)", r
ange = "b6:b72", col_names = F))


#identity matrix
id <- diag(rep(1,68))
```

The next group of data comes from ICCT's Roadmap model:

**"tax"** is gross taxes less subsidies per sector; **"m"** contains projections of imports of ICEV and EV in Brazil; and **"x"** contains projections of exports of ICEVs and EVs in Brazil

```
tax <- as.matrix(read_excel("C://Users//…//MIP2019_67setores.xlsx", she
et = "impostos ativ", range = "c4:c70", col_names = F))
m <- as.data.frame(read_excel("C://Users//…//data_2019.xlsx", sheet= "m
", col_names = T))
x <- as.data.frame(read_excel("C://Users//…//data_2019.xlsx", sheet= "x
", col_names = T))
```

The following data refer to the synthetic sector incorporated in the input-output matrix. **ev_dom** and **ev_imp** are vectors with intermediary use values for a supposed EV industry. These values were detailed in the previous sections. **ev_y** is a scalar that contains the hypothetical output of EV industry for 2019 if it had produced as many vehicles as the ICE industry, used to obtain the technical coefficients presented above.

```
ev_dom <- as.matrix(read_excel("C://Users//…//br_iodata_v4.xlsx", sheet
 = "EV_ind", range = "j3:j70", col_names = F))
ev_imp <- as.matrix(read_excel("C://Users//…//br_iodata_v4.xlsx", sheet
 = "EV_ind", range = "j72:j139", col_names = F))

ev_y <- as.data.frame(261308.906760452) #from ICCT calculation
```

Finally, we created separate vectors for important variables. The uses matrix (u) contains 127 activities, and the 75th column presents final demand values. We employed these values to create a final demand vector by activity (**fd_prod**). Then, we calculated the market share matrix (**mkt_share**) that allows the aggregation of the 127 activities into 67 sectors.

```
fd_prod <- as.data.frame(u[1:126,75]) #domestic demand (product)
row.names(fd_prod) <- label_prod

mkt_share <- t(s[1:126,10:76]/s[1:126,77]) #calculating the market shar
e matrix
colnames(mkt_share) <- label_prod
```

### CALCULATING PRICES FOR DISTINCT CATEGORIES OF VEHICLES

To simulate changes in the demand for vehicles in the 2019–2050 period, prices from different categories of vehicles must interact. Here, we propose a calculation of relative unitary prices by using the ICCT's projections and scenarios.

Vehicles are divided into **LDVs**, comprising passenger cars (PCs) and light commercial vehicles (LCVs), and **HDVs**, comprising buses, medium duty trucks (MDTs), and heavy-duty trucks (HDTs). Vehicles are also categorized by powertrain, into **ICE vehicles** or **EVs**.

First, we calculated the share of output of the ICE automotive industry for each category defined by "activity" in the input-output database. LDVs and HDVs are represented by the 81st and the 82nd activities in the supply matrix, respectively. Column 77 refers to the activity output.

```
y_dom_ldv <- s[81,77]#134027 LDVs
y_dom_hdv <- s[82,77] #63659 HDVs
```

Second, we imported ICCT scenarios and used them to compile the number of vehicles per segment and powertrain in 2019:

```
#Remember to run "scenario_prep.R" first

#Importing ICCT scenario for 2050

scen_raw <- read.csv("C://Users//… //scen_raw.csv")
scen_raw[is.na(scen_raw)] <- 0

N_Bus <- scen_raw$sal_Bus_ICE.Diesel[1] +
  scen_raw$sal_Bus_ICE.Ethanol[1] +
  scen_raw$sal_Bus_ICE.Gasoline[1] +
  scen_raw$sal_Bus_ICE.Biodiesel[1]

N_MDT <- scen_raw$sal_MDT_ICE.Diesel[1] +
  scen_raw$sal_MDT_ICE.Gasoline[1] +
  scen_raw$sal_MDT_ICE.Biodiesel[1]

N_HDT <- scen_raw$sal_HDT_ICE.Diesel[1] +
```

```
  scen_raw$sal_HDT_ICE.Biodiesel[1]

N_PC <- scen_raw$sal_PC_ICE.Diesel[1] +
  scen_raw$sal_PC_ICE.Ethanol[1] +
  scen_raw$sal_PC_ICE.Gasoline[1] +
  scen_raw$sal_PC_PHEV.Gasoline[1]

N_LCV <- scen_raw$sal_LCV_ICE.Diesel[1] +
  scen_raw$sal_LCV_ICE.Ethanol[1] +
  scen_raw$sal_LCV_ICE.Gasoline[1] +
  scen_raw$sal_LCV_ICE.Biodiesel[1]

N_Bus_dom <- N_Bus*(1-m$m_Bus_ice[1])
N_MDT_dom <- N_MDT*(1-m$m_MDT_ice[1])
N_HDT_dom <- N_HDT*(1-m$m_HDT_ice[1])
N_LCV_dom <- N_LCV*(1-m$m_LCV_ice[1])
N_PC_dom  <- N_PC*(1-m$m_PC_ice[1])
```

Then, we calculated the unitary relative prices:

```
### HDVs - Relative price by segment
# MDT and HDT from https://theicct.org/wp-content/uploads/2023/03/cost-
zero-emission-trucks-us-phase-3-mar23.pdf
# Bus from SF-PMSP
1       #MDT-ICE/MDT-ICE rigid, class 4-5
1.7887  #HDT-ICE/MDT-ICE (50% class 8 long-haul + 50% mean(class 6-7, c
lass 8 straight, class 8 short-haul))
1.744   #Bus-ICE/MDT-ICE (From padron ICE bus in Brazil, Euro 6, conver
ted using 5 BRL/USD)
1.43    #MDT-BEV/MDT_ICE
4.36    #HDT-BEV/MDT/ICE   (50% class 8 long-haul + 50% mean(class 6-7,
 class 8 straight, class 8 short-haul))
5.92    #Bus-BEV/MDT-ICE   (BR padron BE-bus BRL 2549000- converted usi
ng 5 BRL/USD)

## Approx unit price of LDVs and HDVs =
# (1)  * (2)   *  (3) / (4)
# (1) price weighted % of segment in HDV/LDV quantities
# (2) % of total output attributed to segment
# (3) output of industry
# (4) number of vehicles sold in segment

prel_mdt_ice <- (1/(N_MDT_dom+(1.744)*N_Bus_dom+(1.7887)*N_HDT_dom))*y_
dom_hdv
prel_hdt_ice <- (1/((1/1.7887)*N_MDT_dom+(1.744/1.7887)*N_Bus_dom+N_HDT
_dom))*y_dom_hdv
prel_bus_ice <- (1/((1/1.744)*N_MDT_dom+N_Bus_dom+(1.7887/1.744)*N_HDT_
dom))*y_dom_hdv

# Check - if the same = ok
prel_bus_ice*N_Bus_dom + prel_hdt_ice*N_HDT_dom + prel_mdt_ice*N_MDT_do
m
```

#Totalproduto 63659

```
y_dom_hdv
```

#Totalproduto 63659

```
#EV
prel_mdt_ev <- (1.43)*prel_mdt_ice
prel_bus_ev <- (5.92/1.744)*prel_bus_ice
prel_hdt_ev <- (4.36/1.7887)*prel_hdt_ice


### LDVs - Relative price by segment
# PC - https://theicct.org/wp-content/uploads/2022/10/ev-cost-benefits-
2035-oct22.pdf
#      https://theicct.org/wp-content/uploads/2021/06/EV_cost_2020_2030
_20190401.pdf
#      https://theicct.org/wp-content/uploads/2021/06/ev_Colorado_cost_
2020_20190613.pdf
# LCV - https://theicct.org/wp-content/uploads/2022/01/cost-ev-vans-pic
kups-us-2040-jan22.pdf

1         #PC-ICE/PC-ICE
1.7035    #LCV-ICE/PC-ICE (assume 1/4 Van gasoline, 1/4 Van diesel, 1/4
 pick-up gas, 1/3, pick-up diesel)
1.4544    #PC-BEV/PC-ICE
2.2544    #LCV-BEV/PC-ICE

#ICE
prel_pc_ice <-  (1/(1*N_PC_dom+(1.7035)*N_LCV_dom))*y_dom_ldv
prel_lcv_ice <- (1/((1/1.7035)*N_PC_dom+N_LCV_dom))*y_dom_ldv

#EV
prel_pc_ev <- (1.4544)*prel_pc_ice
prel_lcv_ev <-(2.2544/1.7035)*prel_lcv_ice

prel_pc_ice*N_PC_dom + prel_lcv_ice*N_LCV_dom
```

#Totalproduto 134027

```
# check if we recover total output value
N_Bus_dom*prel_bus_ice+N_HDT_dom*prel_hdt_ice+N_MDT_dom*prel_mdt_ice+N_
PC_dom*prel_pc_ice+N_LCV_dom*prel_lcv_ice
```

#Totalproduto 197686

```
y_dom_ldv + y_dom_hdv
```

#Totalproduto 197686

```
#ok
```

## PREPARING FINAL DEMAND SCENARIOS

We then made projections of changes in final domestic demand for the 2019–2050 period. Two scenarios were considered: the Baseline (*cenário Base*) and Electrification scenarios (*cenário Eletrificação*). These are from the Roadmap scenario projections explained in the previous section and in the main text. The first step was to calculate the shares of total activity output of LDVs and HDVs that is due to final demand. As above, activities 81 and 82 represented LDVs and HDVs, respectively; 77 is the output column and 75 is the final demand column.

```
pct_fd_ldv  <- u[81,75]/s[81,77]   #percentage of the output "automóvei
s,..." that comes from final demand
pct_fd_hdv <-  u[82,75]/s[82,77]   #percentage of the output "caminhões
 ..." that comes from final demand
```

Then, we added the variations in imports and exports to the scenarios:

```
scen_raw <- scen_raw %>%
colnames(m)[1] <- "CY" #years (2019,2020,...,2050)
colnames(m)[2] <- "Scenario" #BAU or ELECT
  scen_raw <- right_join(scen_raw, m, by = c("Scenario", "CY"))
colnames(x)[1] <- "CY"
colnames(x)[2] <- "Scenario"
  scen_raw <- right_join(scen_raw, x, by = c("Scenario", "CY"))
```

Finally, we can estimate the new domestic demand for both the Baseline and Electrification scenarios.

```
#To obtain final demand for domestically produced ICEVs and EVs:
# ((number of sales in segment * (1-%imports in segment) * relative pri
ce of segment) *
# (% of output sold as final demand)) *
# ( 1 + variation of exports with respect to the initial year) * [% red
uction in EV prices] - for EVs only
```

### A) Baseline scenario

```
df_fd_bau <- scen_raw %>%
  filter(Scenario == "bau") %>%
  mutate(
    bus_ICE = (sal_Bus_ICE.Diesel+sal_Bus_ICE.Ethanol+sal_Bus_ICE.Gasol
ine+sal_Bus_ICE.Biodiesel)*(1-m_Bus_ice)*as.numeric(prel_bus_ice),
    MDT_ICE = (sal_MDT_ICE.Diesel+sal_MDT_ICE.Gasoline+sal_MDT_ICE.Biod
iesel)*(1-m_MDT_ice)*as.numeric(prel_mdt_ice),
    HDT_ICE = (sal_HDT_ICE.Diesel+sal_HDT_ICE.Biodiesel)*(1-m_HDT_ice)*
 as.numeric(prel_hdt_ice),
    LCV_ICE = (sal_LCV_ICE.Diesel+sal_LCV_ICE.Ethanol+sal_LCV_ICE.Gasol
ine+sal_LCV_ICE.Biodiesel)*(1-m_LCV_ice)*as.numeric(prel_lcv_ice),
    PC_ICE = (sal_PC_ICE.Diesel+sal_PC_ICE.Ethanol+sal_PC_ICE.Gasoline+
sal_PC_PHEV.Gasoline)*(1-m_PC_ice)*as.numeric(prel_pc_ice))

df_fd_bau <- df_fd_bau %>%
  mutate(fdice_hdv = (bus_ICE + MDT_ICE + HDT_ICE)*pct_fd_hdv,
                  fd_ice_hdv = fdice_hdv*(1+(0.19087860-exports))) %>
```

```
%
          mutate(fdice_ldv = (LCV_ICE + PC_ICE)*pct_fd_ldv,
        fd_ice_ldv = fdice_ldv*(1+(0.19087860-exports))) %>%
  select(-c(fdice_hdv,fdice_ldv, bus_ICE, MDT_ICE, HDT_ICE, PC_ICE, LCV
_ICE))
```

**df_fd_bau** is a dataframe that contains part of the information necessary for the estimation of the multiplier effects. **fd_ice_hdv** and **fd_ice_ldv** are the new columns that indicate the change in demand for ICE HDVs and LDVs for the simulated period. The same procedure is replicated for HDVs and LDVs in the EV industry:

```
df_fd_bau <- df_fd_bau %>%
  filter(Scenario == "bau") %>%
  mutate(bus_BEV = sal_Bus_BEV*(1-m_Bus_ev)*as.numeric(prel_bus_ev),
         MDT_BEV = sal_MDT_BEV*(1-m_MDT_ev)*as.numeric(prel_mdt_ev),
         HDT_BEV = sal_HDT_BEV*(1-m_HDT_ev)*as.numeric(prel_hdt_ev),
         LCV_BEV = sal_LCV_BEV*(1-m_LCV_ev)* as.numeric(prel_lcv_ev),
         PC_BEV = sal_PC_BEV*(1-m_PC_ev)*as.numeric(prel_pc_ev))

df_fd_bau <- df_fd_bau %>%
  mutate(fdev_hdv = (bus_BEV + MDT_BEV + HDT_BEV)*pct_fd_hdv,
fd_ev_hdv = fdev_hdv*(1+(0.19087860-exports))) %>%
  mutate(fdev_ldv = (LCV_BEV + PC_BEV)*pct_fd_ldv,
  fd_ev_ldv = fdev_ldv*(1+(0.19087860-exports))) %>%
  select(-c(fdev_hdv, fdev_ldv, bus_BEV, MDT_BEV, HDT_BEV, PC_BEV, LCV_
BEV))
```

### B) Electrification scenario

The same procedure applied to Baseline is replicated for the Electrification scenario.

```
#ELECT - ICE
df_fd_elect <- scen_raw %>%
  filter(Scenario == "elect") %>%
  mutate(
    bus_ICE = (sal_Bus_ICE.Diesel+sal_Bus_ICE.Ethanol+sal_Bus_ICE.Gasol
ine+sal_Bus_ICE.Biodiesel)*(1-m_Bus_ice)* as.numeric(prel_bus_ice),
    MDT_ICE = (sal_MDT_ICE.Diesel+sal_MDT_ICE.Gasoline+sal_MDT_ICE.Biod
iesel)*(1-m_MDT_ice)*as.numeric(prel_mdt_ice),
    HDT_ICE = (sal_HDT_ICE.Diesel+sal_HDT_ICE.Biodiesel)*(1-m_HDT_ice)*
 as.numeric(prel_hdt_ice),
    LCV_ICE = (sal_LCV_ICE.Diesel+sal_LCV_ICE.Ethanol+sal_LCV_ICE.Gasol
ine+sal_LCV_ICE.Biodiesel)*(1-m_LCV_ice)*as.numeric(prel_lcv_ice),
    PC_ICE = (sal_PC_ICE.Diesel+sal_PC_ICE.Ethanol+sal_PC_ICE.Gasoline+
sal_PC_PHEV.Gasoline)*(1-m_PC_ice)*as.numeric(prel_pc_ice))

df_fd_elect <- df_fd_elect %>%
  mutate(fdice_hdv = (bus_ICE + MDT_ICE + HDT_ICE)*pct_fd_hdv,
                   fd_ice_hdv = fdice_hdv*(1+(0.19087860-exports))) %>%
  mutate(fdice_ldv = (LCV_ICE + PC_ICE)*pct_fd_ldv,
         fd_ice_ldv = fdice_ldv*(1+(0.19087860-exports))) %>%
  select(-c(fdice_ldv,fdice_hdv, bus_ICE, MDT_ICE, HDT_ICE, PC_ICE, LCV
_ICE))
```

```
#ELECT - EV
df_fd_elect <- df_fd_elect %>%
  filter(Scenario == "elect") %>%
  mutate(bus_BEV = sal_Bus_BEV*(1-m_Bus_ev)*as.numeric(prel_bus_ev),
         MDT_BEV = sal_MDT_BEV*(1-m_MDT_ev)*as.numeric(prel_mdt_ev),
         HDT_BEV = sal_HDT_BEV*(1-m_HDT_ev)*as.numeric(prel_hdt_ev),
         LCV_BEV = sal_LCV_BEV*(1-m_LCV_ev)* as.numeric(prel_lcv_ev),
         PC_BEV = sal_PC_BEV*(1-m_PC_ev)*as.numeric(prel_pc_ev))

df_fd_elect <- df_fd_elect %>%
  mutate(fdev_hdv = (bus_BEV + MDT_BEV + HDT_BEV)*pct_fd_hdv,
                     fd_ev_hdv = fdev_hdv*(1+(0.19087860-exports))) %>%
  mutate( fdev_ldv = (LCV_BEV + PC_BEV)*pct_fd_ldv,
         fd_ev_ldv = fdev_ldv*(1+(0.19087860-exports))) %>%
  select(-c(fdev_hdv,fdev_ldv, bus_BEV, MDT_BEV, HDT_BEV, PC_BEV, LCV_B
EV))
```

By the end of this process, we have four new columns in both **df_fd_bau** and **df_fd_elect** representing the new final demand for ICE HDVs and LDVs and for EV HDVs and LDVs. They are the following: **fd_ice_hdv**, **fd_ice_hdv**, **fd_ev_hdv**, **fd_ev_hdv**.

### Incorporating changes in demand for fuels

The previous estimation exclusively considered alterations in sales of vehicles to calculate final demand in the two scenarios. However, a more complete analysis should assume that changes in vehicles demand also imply changes in fuel demand. As with vehicle categories, the first step was to identify how prices of fuels are related. Four categories were considered, considering both LDVs and HDVs: biofuels, diesel, gasoline, and electricity. Biofuels include ethanol and biodiesel (HVO).

```
N_eth <- 40128188258 #volume of ethanol from scen_raw
N_biodiesel <- 4417302070 # volume of biodiesel from scen_raw

#50 is diesel and biodiesel
#56 is ethanol and others
#46 is Aviation fuel
#47 is Gasoline
#48 is NAFTA
#49 is óleo combustível
#51 is other

bf_output <- s[52,77] #biofuels output

#unitary relative prices of biofuels (biodiesel and ethanol):
prel_eth <- (1*N_eth/(1*N_eth+(5.925/2.589)*N_biodiesel))*bf_output/N_e
th
prel_bd  <- ((5.925/2.589)*N_biodiesel/(1*N_eth+(5.925/2.589)*N_biodies
el))*bf_output/N_biodiesel

#Checking results
N_eth*prel_eth + N_biodiesel*prel_bd
```

Total product 84519

```
bf_output
```

Total product 84519

```
# Output of petroleum refining products
s[46,77]  # 14257 Aviation fuel

s[47,77]  # 103274 Gasoline

s[48,77]  # 10405 NAFTA

s[49,77]  # 22814 óleo combustível

s[50,77]  # 147578 diesel

s[51,77]  # 179269 other


prel_gas <- s[47,77]/8468389227 #gasoline from scen_raw
prel_diesel <- s[50,77]/39755707773 #diesel from scen_raw

#Output of electricity
s[88,77]  # 340823 electricity & gas


prel_elect <- s[88,77]/633317600000 #volume obtained by the Balanço ene
rgético nacional interativo - 2.28 Eletricidade - Produção oferta bruta

# fd of petroleum refining products
fd_prod[46,]  #Aviation fuel (5024.149330)

fd_prod[47,]  #Gasoline (89097.983136)

fd_prod[48,]  #NAFTA(1318.180239)

fd_prod[49,]  # heavy fuel oil - HFO (11354.606867)

fd_prod[50,]  # diesel (5542.683965)

fd_prod[51,] # other (18055.572947)


pct_fd_biof <- fd_prod[56,]/ s[56,77]
pct_fd_gasoline <- fd_prod[47,]/ s[47,77]
pct_fd_diesel <- fd_prod[50,]/ s[50,77]
pct_fd_elect <- fd_prod[88,]/s[88,77]
```

With the unitary prices of each fuel source, we can recalculate scenarios by considering both vehicles' and fuels' final demand. Since these scenarios are the focus of the analysis, they are employed as the baseline to detail the methodological procedures in the rest of this document.

```r
#Baseline -- FINAL DEMAND FOR 2050

df_fd_bau_fuels <- scen_raw %>%
  filter(Scenario == "bau") %>%
  mutate(
    bus_ICE = (sal_Bus_ICE.Diesel+sal_Bus_ICE.Ethanol+sal_Bus_ICE.Gasol
ine+sal_Bus_ICE.Biodiesel)*(1-m_Bus_ice)*as.numeric(prel_bus_ice),
    MDT_ICE = (sal_MDT_ICE.Diesel+sal_MDT_ICE.Gasoline+sal_MDT_ICE.Biod
iesel)*(1-m_MDT_ice)*as.numeric(prel_mdt_ice),
    HDT_ICE = (sal_HDT_ICE.Diesel+sal_HDT_ICE.Biodiesel)*(1-m_HDT_ice)*
 as.numeric(prel_hdt_ice),
    LCV_ICE = (sal_LCV_ICE.Diesel+sal_LCV_ICE.Ethanol+sal_LCV_ICE.Gasol
ine+sal_LCV_ICE.Biodiesel)*(1-m_LCV_ice)*as.numeric(prel_lcv_ice),
    PC_ICE = (sal_PC_ICE.Diesel+sal_PC_ICE.Ethanol+sal_PC_ICE.Gasoline+
sal_PC_PHEV.Gasoline)*(1-m_PC_ice)*as.numeric(prel_pc_ice))

df_fd_bau_fuels <- df_fd_bau_fuels %>%
  mutate(fdice_hdv = (bus_ICE + MDT_ICE + HDT_ICE)*pct_fd_hdv,
         fd_ice_hdv = fdice_hdv*(1+(exports-0.19087860))) %>%
  mutate(fdice_ldv = (LCV_ICE + PC_ICE)*pct_fd_ldv,
         fd_ice_ldv = fdice_ldv*(1+(exports-0.19087860))) %>%
  select(-c(fdice_hdv,fdice_ldv, bus_ICE, MDT_ICE, HDT_ICE, PC_ICE, LCV
_ICE))

#Demand for EV - LDV & HDV - Two new columns are created, one for each
subcategory


df_fd_bau_fuels <- df_fd_bau_fuels %>%
  filter(Scenario == "bau") %>%
  mutate(bus_BEV = sal_Bus_BEV*(1-m_Bus_ev)*as.numeric(prel_bus_ev),
         MDT_BEV = sal_MDT_BEV*(1-m_MDT_ev)*as.numeric(prel_mdt_ev),
         HDT_BEV = sal_HDT_BEV*(1-m_HDT_ev)*as.numeric(prel_hdt_ev),
         LCV_BEV = sal_LCV_BEV*(1-m_LCV_ev)* as.numeric(prel_lcv_ev),
         PC_BEV = sal_PC_BEV*(1-m_PC_ev)*as.numeric(prel_pc_ev))

df_fd_bau_fuels <- df_fd_bau_fuels %>%
  mutate(fdev_hdv = (bus_BEV + MDT_BEV + HDT_BEV)*pct_fd_hdv,
         fd_ev_hdv = fdev_hdv*(1+(exports-0.19087860))) %>%
  mutate(fdev_ldv = (LCV_BEV + PC_BEV)*pct_fd_ldv,
         fd_ev_ldv = fdev_ldv*(1+(exports-0.19087860))) %>%
  select(-c(fdev_hdv, fdev_ldv, bus_BEV, MDT_BEV, HDT_BEV, PC_BEV, LCV_
BEV))

#Demand for fuels

df_fd_bau_fuels <- df_fd_bau_fuels %>%
  filter(Scenario == "bau") %>%
  mutate(
    fd_biof =  (ethanol*as.numeric(prel_eth)+biodiesel*as.numeric(prel_
bd))*as.numeric(pct_fd_biof),
    fd_gasoline = (gasoline*as.numeric(pct_fd_gasoline)*prel_gas),
    fd_diesel = (diesel*as.numeric(pct_fd_diesel)*prel_diesel),
    fd_elect = (101599.012626+(electricity*pct_fd_elect*(as.numeric(pre
```

```
l_elect)))))

View(df_fd_bau_fuels)

#ELECTRIFICATION (ELECT) -- FINAL DEMAND FOR 2050

#Demand for ICE - LDV & HDV - Two new columns are created, one for each
 subcategory

df_fd_elect_fuels <- scen_raw %>%
  filter(Scenario == "elect") %>%
  mutate(
    bus_ICE = (sal_Bus_ICE.Diesel+sal_Bus_ICE.Ethanol+sal_Bus_ICE.Gasol
ine+sal_Bus_ICE.Biodiesel)*(1-m_Bus_ice)* as.numeric(prel_bus_ice),
    MDT_ICE = (sal_MDT_ICE.Diesel+sal_MDT_ICE.Gasoline+sal_MDT_ICE.Biod
iesel)*(1-m_MDT_ice)*as.numeric(prel_mdt_ice),
    HDT_ICE = (sal_HDT_ICE.Diesel+sal_HDT_ICE.Biodiesel)*(1-m_HDT_ice)*
 as.numeric(prel_hdt_ice),
    LCV_ICE = (sal_LCV_ICE.Diesel+sal_LCV_ICE.Ethanol+sal_LCV_ICE.Gasol
ine+sal_LCV_ICE.Biodiesel)*(1-m_LCV_ice)*as.numeric(prel_lcv_ice),
    PC_ICE = (sal_PC_ICE.Diesel+sal_PC_ICE.Ethanol+sal_PC_ICE.Gasoline+
sal_PC_PHEV.Gasoline)*(1-m_PC_ice)*as.numeric(prel_pc_ice))

df_fd_elect_fuels <- df_fd_elect_fuels %>%
  mutate(fdice_hdv = (bus_ICE + MDT_ICE + HDT_ICE)*pct_fd_hdv,
         fd_ice_hdv = fdice_hdv*(1+(exports-0.19087860))) %>%
  mutate(fdice_ldv = (LCV_ICE + PC_ICE)*pct_fd_ldv,
         fd_ice_ldv = fdice_ldv*(1+(exports-0.19087860))) %>%
  select(-c(fdice_ldv,fdice_hdv, bus_ICE, MDT_ICE, HDT_ICE, PC_ICE, LCV
_ICE))

#Demand for EV - LDV & HDV - Two new columns are created, one for each
subcategory

df_fd_elect_fuels <- df_fd_elect_fuels %>%
  filter(Scenario == "elect") %>%
  mutate(bus_BEV = sal_Bus_BEV*(1-m_Bus_ev)*as.numeric(prel_bus_ev),
         MDT_BEV = sal_MDT_BEV*(1-m_MDT_ev)*as.numeric(prel_mdt_ev),
         HDT_BEV = sal_HDT_BEV*(1-m_HDT_ev)*as.numeric(prel_hdt_ev),
         LCV_BEV = sal_LCV_BEV*(1-m_LCV_ev)* as.numeric(prel_lcv_ev),
         PC_BEV = sal_PC_BEV*(1-m_PC_ev)*as.numeric(prel_pc_ev))

df_fd_elect_fuels <- df_fd_elect_fuels %>%
  mutate(fdev_hdv = (bus_BEV + MDT_BEV + HDT_BEV)*pct_fd_hdv,
         fd_ev_hdv = fdev_hdv*(1+(exports-0.19087860))) %>%
  mutate( fdev_ldv = (LCV_BEV + PC_BEV)*pct_fd_ldv,
          fd_ev_ldv = fdev_ldv*(1+(exports-0.19087860))) %>%
  select(-c(fdev_hdv,fdev_ldv, bus_BEV, MDT_BEV, HDT_BEV, PC_BEV, LCV_B
EV))

# Demand for fuels

df_fd_elect_fuels <- df_fd_elect_fuels %>%
  filter(Scenario == "elect") %>%
```

```
  mutate(
    fd_biof =  (ethanol*as.numeric(prel_eth)+biodiesel*as.numeric(prel_
bd))*as.numeric(pct_fd_biof),
    fd_gasoline = (gasoline*as.numeric(pct_fd_gasoline)*prel_gas),
    fd_diesel = (diesel*as.numeric(pct_fd_diesel)*prel_diesel),
    fd_elect = (101599.012626+(electricity*pct_fd_elect*(as.numeric(pre
l_elect)))))

View(df_fd_elect_fuels)
```

## CHANGING THE ORIGINAL FINAL DEMAND (ACTIVITY) BY ADDING NEW RESULTS AND REPLICATING IN TIME

Demands for ICE vehicles (HDV and LDV) and for fuels until 2050 were then incorporated in the final demand vector for activities. As our aim is to focus on a unique EV sector that contains both HDV and LDV values, and since there is not an EV sector in the original matrix, results for EVs will be incorporated directly in the final demand vector for sectors (EV(HDV) + EV (LDV)) afterwards. The following process describes the creation of a new vector of final demand for each year from 2019 to 2050. For each year, the final demand for ICE-LDVs (row 81), ICE-HDVs (row 82), diesel (row 50), gasoline (row 47), biofuels (row 58), and electricity (row 88) are replaced by the new demands calculated according to the ICCT's Roadmap model for both scenarios.

```
#creating a list in which each object is a year from 2019 to 2050
fdfuels_list_bau <- list()
fdfuels_list_elect <- list()
```

### A) Baseline

```
#Replacing the demand for product by the projected demand

for(i in 1:nrow(df_fd_bau_fuels)){
  fdfuels_list_bau[[i]] <- fd_prod[,1]
  fdfuels_list_bau[[i]] <- replace(fdfuels_list_bau[[i]],50,df_fd_bau_f
uels$fd_diesel[i])
  fdfuels_list_bau[[i]] <- replace(fdfuels_list_bau[[i]],47,df_fd_bau_f
uels$fd_gasoline[i])
  fdfuels_list_bau[[i]] <- replace(fdfuels_list_bau[[i]],56,df_fd_bau_f
uels$fd_biof[i])
  fdfuels_list_bau[[i]] <- replace(fdfuels_list_bau[[i]],88,df_fd_bau_f
uels$fd_elect[i])
  fdfuels_list_bau[[i]] <- replace(fdfuels_list_bau[[i]],81,df_fd_bau_f
uels$fd_ice_ldv[i])
  fdfuels_list_bau[[i]] <- replace(fdfuels_list_bau[[i]],82,df_fd_bau_f
uels$fd_ice_hdv[i])
}

fdtime_bau_fuels <- do.call(rbind,fdfuels_list_bau)


#Calculating for each year a new demand for sector, considering the mar
ket share matrix:
```

```r
fd_time_bau_fuels <- matrix(0, nrow = 67, ncol = 32)
for(i in 1:nrow(fdtime_bau_fuels)){
  fd_time_bau_fuels[,i] <- mkt_share%*% as.matrix(fdtime_bau_fuels[i,])
}
colnames(fd_time_bau_fuels) <- 2019:2050
rownames(fd_time_bau_fuels) <- label_sector
```

**fd_time_bau_fuels** contains the new demand for sector (row) per year (column) in the Baseline scenario. However, we still need to incorporate the final demand for EVs for each year. To do so, we created a new row in each matrix of **fd_time_bau_fuels** that contains the final demand for EVs.

```r
ev_fd_bau_fuels <- df_fd_bau_fuels$fd_ev_hdv + df_fd_bau_fuels$fd_ev_ld
v
fd_time_bau_fuels <- rbind(ev_fd_bau_fuels,fd_time_bau_fuels) #this is
the final demand (by sector) until 2050
```

### B) Electrification

We repeat the procedure.

```r
for(i in 1:nrow(df_fd_elect_fuels)){
  fdfuels_list_elect[[i]] <- fd_prod[,1]
  fdfuels_list_elect[[i]] <- replace(fdfuels_list_elect[[i]],50,df_fd_e
lect_fuels$fd_diesel[i])#fuel
  fdfuels_list_elect[[i]] <- replace(fdfuels_list_elect[[i]],47,df_fd_e
lect_fuels$fd_gasoline[i])
  fdfuels_list_elect[[i]] <- replace(fdfuels_list_elect[[i]],56,df_fd_e
lect_fuels$fd_biof[i])
  fdfuels_list_elect[[i]] <- replace(fdfuels_list_elect[[i]],88,df_fd_e
lect_fuels$fd_elect[i])
  fdfuels_list_elect[[i]] <- replace(fdfuels_list_elect[[i]],81,df_fd_e
lect_fuels$fd_ice_ldv[i])#cars
  fdfuels_list_elect[[i]] <- replace(fdfuels_list_elect[[i]],82,df_fd_e
lect_fuels$fd_ice_hdv[i])
}

fdtime_elect_fuels <- do.call(rbind,fdfuels_list_elect)

fd_time_elect_fuels <- matrix(0, nrow = 67, ncol = 32)
for(i in 1:nrow(fdtime_elect_fuels)){
  fd_time_elect_fuels[,i] <- mkt_share%*% as.matrix(fdtime_elect_fuels[
i,])
}
colnames(fd_time_elect_fuels) <- 2019:2050
rownames(fd_time_elect_fuels) <- label_sector

ev_fd_elect_fuels <- df_fd_elect_fuels$fd_ev_hdv + df_fd_elect_fuels$fd
_ev_ldv
fd_time_elect_fuels <- rbind(ev_fd_elect_fuels,fd_time_elect_fuels)


#checking totals for BAU and ELECT scenarios
```

```
totfd_bau <- colSums(fd_time_bau_fuels)
totfd_elect <- colSums(fd_time_elect_fuels)
```

### PREPARING THE LEONTIEF MATRIX WITH THE SYNTHETIC EV INDUSTRY

In the following code, a new column is added in the domestic use matrix. This column represents a new (synthetic) sector for EV manufacturing and contains estimated values of the intermediary use of goods and services that the latter demands from all the other sectors in the economy. Since matrices have to be balanced, a row with the same values is also added. Both the column and the row are divided by a large number so that this sector becomes irrelevant in terms of value demanded and supplied. This is an important procedure because as the use matrix (Adom) is transformed into a coefficient matrix (Bdom), row values will present lower values than columns. These values assure that the contribution of the EV industry in terms of forward linkages is irrelevant but conserves its contribution in terms of backward linkages. For more details on this method see Kim (2011) and Kim et al. (2017; 2019).

```
Adom_ev <- as.data.frame(Adom) %>%
   add_row(.before = 1)
Adom_ev <- cbind(ev_dom/1000000000,Adom_ev) #adding the EV sector in ro
ws and columns
Adom_ev[1,] <- t(ev_dom)/1000000000

rownames(Adom_ev) <- c("EV",label_sector)
colnames(Adom_ev) <- c("EV", label_sector)

Y_ev <- cbind((ev_y/1000000000),Y) #adding EV output to Y
Y_ev <- as.matrix(Y_ev)

Bdom <- mapply("/",Adom_ev, Y_ev) #Calculating the coefficient matrix
Zdom = solve(id - Bdom)                ## Leontief inverse matrix
```

### CALCULATING EV OUTPUT FOR THE SCENARIOS AND JOB MULTIPLIERS FOR THE MAIN SECTORS

In this section, we will indicate how to calculate employment multipliers, but there are several other possibilities to be simulated. In the following code, the employment per output vector, or direct employment coefficient vector (**"l"**), also includes a coefficient for the EV industry. The chosen value for the EV employment coefficient is based on the literature that compares jobs generated by ICE and EV industries, presented in the main report. In this simulation, we employ the mean value presented in Table 1 of the main report, equal to 70.35%.

```
l <- (L/Y)
colnames(l) <- label_sector
ev_lcoef <- l[,33]*0.7035 #ev direct employment coefficient (based on l
iterature average)
l <- t(cbind(ev_lcoef,l)) # 68 sectors "l" vector
```

We can now proceed to calculate ICE and EV multiplier effects (direct and indirect) on employment by using the Leontief matrix (Zdom), in which the first column and row refers to the EV industry and the 34th refers to the ICE industry. **lmult_tot** indicates the contribution of each sector (ICE and EV) for employment generation per monetary unit of output.

```
mult_ev <- Zdom[,1]*l
mult_icev <- Zdom[,34]*l

lmult <- cbind(mult_ev,mult_icev)
lmult <- as.data.frame(lmult)
colnames(lmult)[1] <- "EV"
colnames(lmult)[2] <- "ICEV"

lmult_tot <- colSums(lmult)
view(lmult_tot)
```

We can also estimate the trajectory of output in the two proposed scenarios by looping the original formula Y = Z.fd:

```
prod_list_bau_fuels <- list()
prod_list_elect_fuels <- list()

for (i in 1:ncol(fd_time_bau_fuels)){
  prod_list_bau_fuels[[i]] <- Zdom %*% fd_time_bau_fuels[,i]
}
for (i in 1:ncol(fd_time_elect_fuels)){
  prod_list_elect_fuels[[i]] <- Zdom %*% fd_time_elect_fuels[,i]
}
```

Finally, we can calculate the new output and the number of jobs generated in both scenarios. Tables **y_bau_fuels** and **l_bau_fuels** have 32 rows (years) and 68 columns (sectors) and present results for the Baseline scenario. The same is valid for the Electrification scenario. It is important to stress here that changes in output and employment depend exclusively on changes in vehicles and fuels demand during the period, which impact other sectors via backward linkages only. By applying *rowSums()* to the tables we can compute the total output and employment by year in both scenarios. These are expressed in **y_tot_baufuels** and **l_tot_baufuels** for the Baseline scenario.

```
#BAU (Baseline)
y_bau_fuels <- do.call(cbind,prod_list_bau_fuels)     ## output
l_bau_fuels <- as.numeric(l)*y_bau_fuels                # employment

y_bau_fuels <- t(y_bau_fuels)
l_bau_fuels <- t(l_bau_fuels)

colnames(y_bau_fuels) <- c("EV", label_sector)
colnames(l_bau_fuels) <- c("EV", label_sector)
rownames(y_bau_fuels) <- c(2019:2050)
rownames(l_bau_fuels) <- c(2019:2050)

#ELECT (Electrification)
y_elect_fuels <- do.call(cbind,prod_list_elect_fuels)     ## output
l_elect_fuels <- as.numeric(l)*y_elect_fuels                # employment
```

```r
y_elect_fuels <- t(y_elect_fuels)
l_elect_fuels <- t(l_elect_fuels)

colnames(y_elect_fuels) <- c("EV", label_sector)
colnames(l_elect_fuels) <- c("EV", label_sector)
rownames(y_elect_fuels) <- c(2019:2050)
rownames(l_elect_fuels) <- c(2019:2050)

#Getting totals PER YEAR

#BAU
tot_baufuels <- rowSums(y_bau_fuels)
l_tot_baufuels <- rowSums(l_bau_fuels)

#ELECT

tot_electfuels <- rowSums(y_elect_fuels)
l_tot_electfuels <- rowSums(l_elect_fuels)
```

### SENSITIVITY ANALYSIS: BATTERIES AND EXPORTS

To better assess the results, we propose a sensitivity analysis that considers (i) a change in the size of the domestic component of batteries used in EV production, and (ii) a change in the export trend for the Electrification scenario, which we replace with the Baseline exports trajectory (which tends to zero).

In the first case, the procedure implies the substitution of the coefficient that defines inputs demanded by the sector called "*Fabricação de Máquinas e Equipamentos Elétricos*" in the coefficient matrix Bdom. **scen_batt** contains three different trajectories for the domestic component of batteries: low, good, and optimistic, plotted in Box 1 of the main report. We analyze the first two. As values are presented as technical coefficients of the EV industry's intermediate demand for electric batteries, we multiplied them by the EV industry output (**ev_y**) to obtain values in monetary units. We divided the results by a large number so that they can be used in input-output procedures to build the synthetic sector. The final step is to construct a list that contains one value for each year analyzed (from 2019 to 2050, meaning 31 years) and substitute each value in the original matrices with these new results.

```r
scen_batt <- read_excel("C://…ev//br_iodata_v4.xlsx", sheet= "EV_batt_d
om", range= "a9:af12", col_names = T)

scen_batt_low <- scen_batt[1,-1]
scen_batt_low <- t(as.matrix(scen_batt_low))%*%as.matrix(ev_y)
scen_batt_low <- scen_batt_low/1000000000
scen_batt_low <- as.list(scen_batt_low)

scen_batt_good <- scen_batt[2,-1]
scen_batt_good <- t(as.matrix(scen_batt_good))%*%as.matrix(ev_y)
scen_batt_good <- scen_batt_good/1000000000
scen_batt_good <- as.list(scen_batt_good)
```

```r
# Create an empty list to store the matrices
bat_low <- vector("list", 31)
bat_good <- vector("list", 31)

Adom_ev <- as.matrix(Adom_ev)
Y_ev <- (as.matrix(Y_ev))

y_ev_list <- list()

#BATT CHANGE = LOW

for (i in 1:31) {
  bat_low[[i]] <- matrix(Adom_ev, nrow = nrow(Adom_ev), ncol = ncol(Ado
m_ev))
}
for (i in 1:31) {
  bat_low[[i]][32, 1] <- scen_batt_low[[i]]
  bat_low[[i]][1, 32] <- scen_batt_low[[i]]
}
# Checking results...
elements_low <- numeric(length(bat_low))
for (i in 1:length(bat_low)) {
  matrix_i <- bat_low[[i]]
  element <- matrix_i[1, 32]
  elements_low[i] <- element
}
print(elements_low)

#BATT CHANGE = GOOD

# Create copies of Y_ev and add them to the list
for (i in 1:31) {
  y_ev_list[[i]] <- matrix(Y_ev, nrow = nrow(Y_ev), ncol = ncol(Y_ev))
}

for (i in 1:31) {
  bat_good[[i]] <- matrix(Adom_ev, nrow = nrow(Adom_ev), ncol = ncol(Ad
om_ev))
}
for (i in 1:31) {
  bat_good[[i]][32, 1] <- scen_batt_good[[i]]
  bat_good[[i]][1, 32] <- scen_batt_good[[i]]
}

# Checking results...
elements_good <- numeric(length(bat_good))
for (i in 1:length(bat_good)) {
  matrix_i <- bat_good[[i]]
  element <- matrix_i[1, 32]
  elements_good[i] <- element
}
print(elements_good)

teste <- bat_good[[2]]
```

```
bat_good[[i]] == Adom_ev


##NEW BDOM MATRICES

B_batt_low <- list()
for (i in 1:31) {
  B_batt_low[[i]] <- matrix(0, nrow = 68, ncol = 68)  # Initialize a 68
x68 matrix with zeros

  for (j in 1:68) {
    B_batt_low[[i]][,j] <- bat_low[[i]][, j] / y_ev_list[[i]][,j]
  }
}

B_batt_low[[1]][,1]==Bdom[,1]
B_batt_low[[1]][,2]==Bdom[,2]
B_batt_low[[15]][,34]==Bdom[,34]

B_batt_good <- list()
for (i in 1:31) {
  B_batt_good[[i]] <- matrix(0, nrow = 68, ncol = 68)  # Initialize a 6
8x68 matrix with zeros

  for (j in 1:68) {
    B_batt_good[[i]][, j] <- bat_good[[i]][, j] / y_ev_list[[i]][,j]
  }
}
#checking..
B_batt_good[[1]][,1]==Bdom[,1]
B_batt_good[[1]][,2]==Bdom[,2]
B_batt_good[[15]][,34]==Bdom[,34]

#it's ok, finally!

Z_batt_low <- list()
for (i in 1:length(bat_low)) {
  Z_batt_low[[i]] <- solve(id-B_batt_low[[i]])
}

Z_batt_good <- list()
for (i in 1:length(bat_good)) {
  Z_batt_good[[i]] <- solve(id-B_batt_good[[i]])
}

leontief_list_low <- c(list(Zdom), Z_batt_low)
leontief_list_good <- c(list(Zdom), Z_batt_good)
```

With the new Leontieff matrices, the scenarios can be recalculated. First, we found employment multipliers, then we recalculated employment and output for the Electrification scenario.

```
#SCENARIO LOW
```

```r
# EVs
lmult_ev_low <- list()

for(i in 1:length(leontief_list_low)){
  multiplier_effect <- leontief_list_low[[i]][,1] * l
  lmult_ev_low[[i]] <- multiplier_effect
}
df_lmult_evlow<- as.data.frame(do.call(cbind, lmult_ev_low))
tot_lmult_evlow <- colSums(df_lmult_evlow) # multipliers by year


#SCENARIO GOOD
# EVs
lmult_ev_good <- list()

for(i in 1:length(leontief_list_good)){
  multiplier_effect <- leontief_list_good[[i]][,1] * l
  lmult_ev_good[[i]] <- multiplier_effect
}
df_lmult_evgood <- as.data.frame(do.call(cbind, lmult_ev_good))
tot_lmult_evgood <- colSums(df_lmult_evgood) # multipliers by year


####  Calculating Output and employment only for the ELECT scenario

prod_good_elect <- list()
prod_low_elect <- list()

#good
for (i in 1:ncol(fd_time_elect_fuels)){
  prod_good_elect[[i]] <- leontief_list_good[[i]] %*% fd_time_elect_fue
ls[,i]
}
y_elect_good <- do.call(cbind,prod_good_elect)     ## output
l_elect_good <- as.numeric(l)*y_elect_good                    ## employm
ent

y_elect_good <- t(y_elect_good)    ## output
l_elect_good <- t(l_elect_good)                  ## employment

y_tot_good <- as.data.frame(rowSums(y_elect_good))
l_tot_good <- as.data.frame(rowSums(l_elect_good))

#low
for (i in 1:ncol(fd_time_elect_fuels)){
  prod_low_elect[[i]] <- leontief_list_low[[i]] %*% fd_time_elect_fuels
[,i]
}

y_elect_low <- do.call(cbind,prod_low_elect)     ## output
l_elect_low <- as.numeric(l)*y_elect_low ## employment

y_elect_low <- t(y_elect_low)    ## output
l_elect_low <- t(l_elect_low)                  ## employment
```

```r
#Getting totals PER YEAR
y_tot_low <- as.data.frame(rowSums(y_elect_low))
l_tot_low <- as.data.frame(rowSums(l_elect_low))
```

The sensitivity analysis also includes the change in exports for the Electrification scenario. In the Baseline scenario, exports tended to fall as a result of a loss of competitivity in external markets. We replaced the Electrification scenario's stable exports trend with this falling trajectory (**bauexports**).

```r
df_fd_export <- df_fd_elect_fuels %>%
  filter(Scenario == "elect") %>%
  mutate(bus_BEV = sal_Bus_BEV*(1-m_Bus_ev)*as.numeric(prel_bus_ev),
         MDT_BEV = sal_MDT_BEV*(1-m_MDT_ev)*as.numeric(prel_mdt_ev),
         HDT_BEV = sal_HDT_BEV*(1-m_HDT_ev)*as.numeric(prel_hdt_ev),
         LCV_BEV = sal_LCV_BEV*(1-m_LCV_ev)* as.numeric(prel_lcv_ev),
         PC_BEV = sal_PC_BEV*(1-m_PC_ev)*as.numeric(prel_pc_ev))

new_exports <- df_fd_bau_fuels$exports

df_fd_export <- df_fd_export %>%
  mutate(bauexports = new_exports) %>%
  mutate(fdev_hdv = (bus_BEV + MDT_BEV + HDT_BEV)*pct_fd_hdv,
         fd_ev_hdv = fdev_hdv*(1+(bauexports-0.19087860))) %>%
  mutate( fdev_ldv = (LCV_BEV + PC_BEV)*pct_fd_ldv,
          fd_ev_ldv = fdev_ldv*(1+(bauexports-0.19087860))) %>%
  select(-c(fdev_hdv,fdev_ldv, bus_BEV, MDT_BEV, HDT_BEV, PC_BEV, LCV_B
EV))

fd_list_export <- list()
#Replacing the demand for product "Automobiles.." and product "Trucks..
" by the projected demand (fd_ice_ldv and fd_ice_hdv, respectively)
for(i in 1:nrow(df_fd_export)){
  fd_list_export[[i]] <- fd_prod[,1]
  fd_list_export[[i]] <- replace(fd_list_export[[i]],81,df_fd_export$fd
_ice_ldv[i])
  fd_list_export[[i]] <- replace(fd_list_export[[i]],82,df_fd_export$fd
_ice_hdv[i])
}

fdtime_export <- do.call(rbind,fd_list_export)
fd_time_export <- matrix(0, nrow = 67, ncol = 32)

for(i in 1:nrow(fdtime_export)){
  fd_time_export[,i] <- mkt_share%*% as.matrix(fdtime_export[i,])
}

#We are now adding demand for EV by creating a new row

ev_fd_export <- df_fd_export$fd_ev_hdv + df_fd_export$fd_ev_ldv
fd_time_export <- rbind(ev_fd_export,fd_time_export) #this is the final
 demand (by sector) until 2050
```

```
### checking totals
totfd_export <- colSums(fd_time_export)

prod_list_export <- list()

for (i in 1:ncol(fd_time_export)){
  prod_list_export[[i]] <- Zdom %*% fd_time_export[,i]
}

#### Now, we can calculate main output variables

## SCENARIO Baseline

y_export <- do.call(cbind,prod_list_export)      ## output
l_export <- as.numeric(l)*y_export                       ## employment

y_export <- t(y_export)
l_export <- t(l_export)

tot_export <- rowSums(y_export)
l_tot_export <- rowSums(l_export)
```

Finally, we assessed gender differentiation of the jobs generated in the scenarios. For this, we used the gender proportion of the Brazilian formal job market according to official data (Brazil, 2019). **gender_ev** contains the proportions of the male (column 1) and female (column 2) labor force for all 68 matrix sectors. We multiplied total jobs by these proportions for the 31 years to estimate the impacts of the EV industry on occupations by gender. Therefore, the assumption is that gender proportions by sector do not change during the period and the effect is related to the number of jobs generated in each sector. Since there is no previous data on gender proportion concerning EV industry, we assumed that it replicates proportions in the ICE industry in the first year.

```
gender_ev <- read_excel("C://Users…//gender_ev.xlsx", sheet = 1)
ev_perc_gender <- gender_ev %>% ##applying the same gender division of
ICE
  filter(label == "Fabricação de automóveis, caminhões e ônibus, exceto
 peças")

gender_ev <- rbind(ev_perc_gender, gender_ev)
gender_ev <- gender_ev %>%
  select(5,6)
row.names(gender_ev) <- c("EV", label_sector)


emp_men_bau <- gender_ev$perc_masc*t(l_bau_fuels)
emp_men_elect <- gender_ev$perc_masc*t(l_elect_fuels)
emp_men_batt <- gender_ev$perc_masc*t(l_elect_good)
emp_men_export <- gender_ev$perc_masc*t(l_export)
emp_women_bau  <-  gender_ev$perc_fem*t(l_bau_fuels)
emp_women_elect <-gender_ev$perc_fem*t(l_elect_fuels)
emp_women_batt <- gender_ev$perc_fem*t(l_elect_good)
```

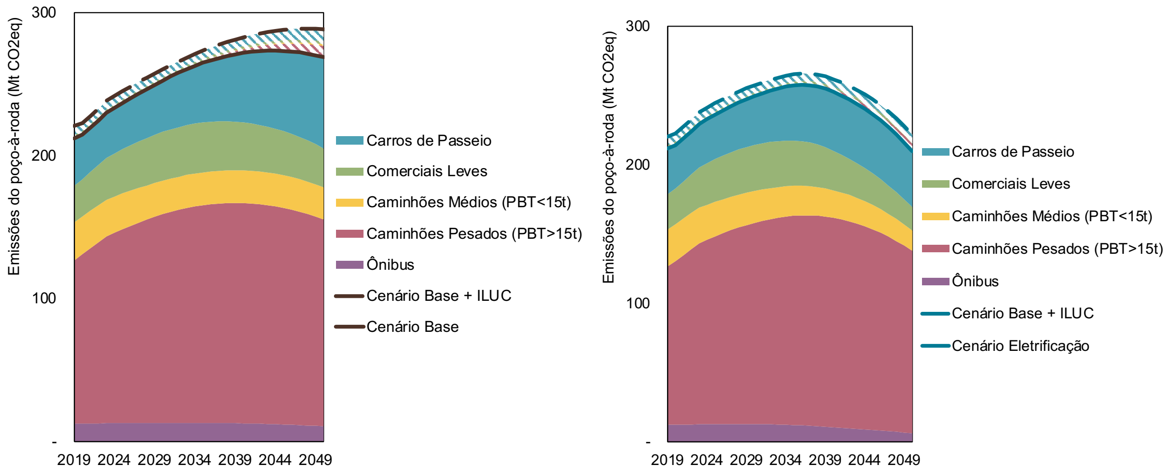
```r
emp_women_export <- gender_ev$perc_fem*t(l_export)

emp_gender <- list(emp_men_bau,emp_men_elect,emp_men_batt,emp_men_expor
t,
                        emp_women_bau, emp_women_elect, emp_women_batt,
 emp_women_export)

emp_gender <- map(emp_gender, colSums)
emp_gender <-do.call(rbind,emp_gender)
emp_gender <- t(emp_gender)
colnames(emp_gender) <- c("emp_men_bau","emp_men_elect","emp_men_batt",
"emp_men_export",
                        "emp_women_bau", "emp_women_elect", "emp_women_
batt", "emp_women_export")
```

## SUPPLEMENTARY RESULTS

This final section provides additional results to those in the main report. The figures below do not present new information and results but rather complement the main report.

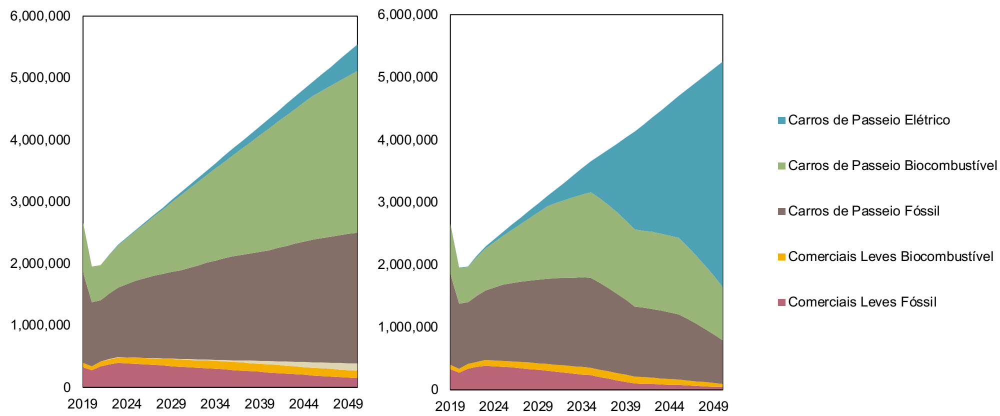
**Error! Reference source not found.** plots the total well-to-wheel emissions from road transportation by segment. These are the same values from Figure 4 in the main report. The figure distinguishes between fuel and electricity production and tailpipe emissions (solid lines) and ILUC emissions from biofuels (dashed lines).

**FIGURE A1. WELL-TO-WHEEL GREENHOUSE GAS EMISSIONS FOR ROAD TRANSPORTATION BY SEGMENT IN THE BASELINE SCENARIO (LEFT) AND ELECTRIFICATION SCENARIO (RIGHT)**



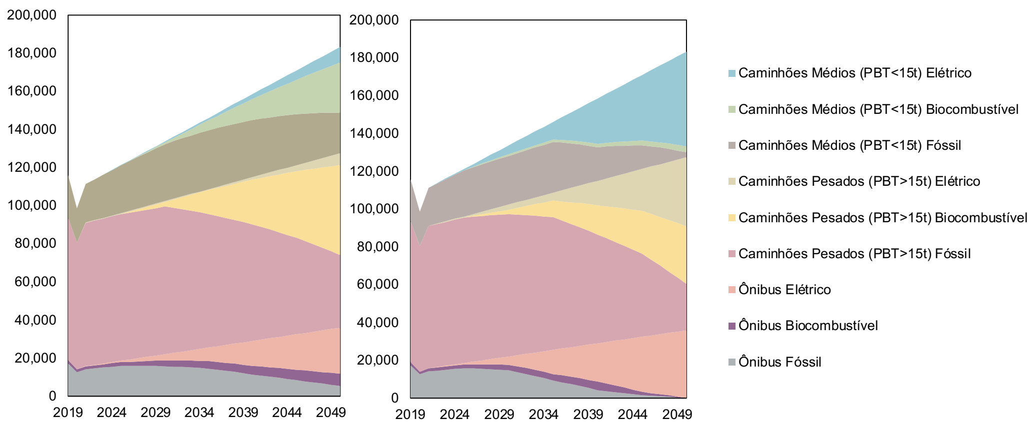

**Error! Reference source not found.** shows the evolution of light-duty vehicle sales by segment (passenger cars and light commercial vehicles) and powertrain (electric, ICE using fossil fuels, and ICE using biofuels). The left panel shows the sales in the Baseline scenario and the right panel the Electrification scenario. Both graphs show how prominent passenger vehicles are in total sales, and therefore crucial for industry growth. Notably, the sales growth rates are the same in the two scenarios; only the powertrain shares in each segment vary.

**FIGURE A2. EVOLUTION OF LIGHT-DUTY VEHICLE SALES BY SEGMENT AND POWERTRAIN IN THE BASELINE SCENARIO (LEFT) AND ELECTRIFICATION SCENARIO (RIGHT)**



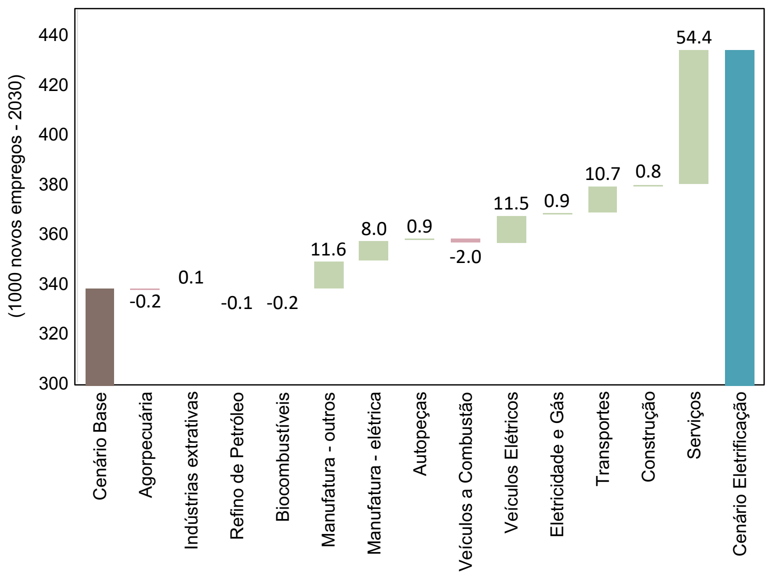

**Error! Reference source not found.** presents projected sales by segment and powertrain in the Baseline (left) and Electrification scenarios (right) for heavy-duty vehicles (that is, medium trucks below 16 t GVW, heavy trucks above 16 t GVW, and buses). Heavy trucks are the largest segment among heavy-duty vehicles.

**FIGURE A3. EVOLUTION OF HEAVY-DUTY VEHICLE SALES BY SEGMENT AND POWERTRAIN IN THE BASELINE SCENARIO (LEFT) AND ELECTRIFICATION SCENARIO (RIGHT)**



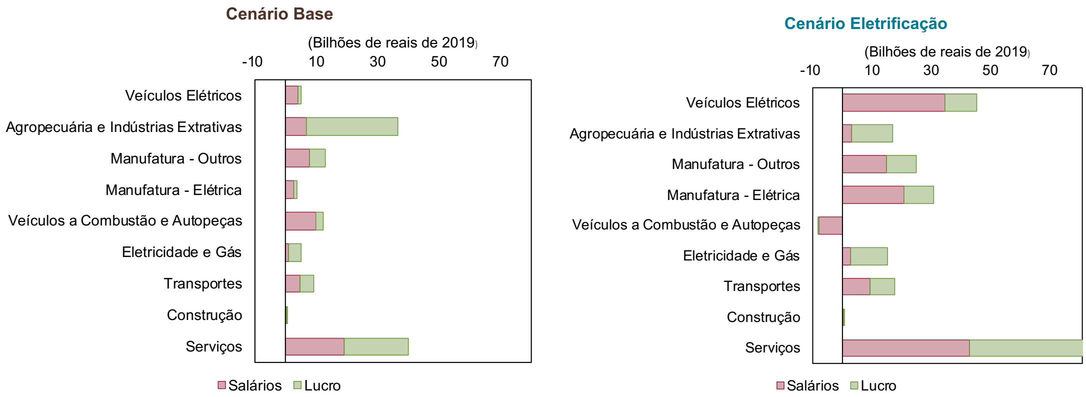

**Error! Reference source not found.** provides greater detail on the industry composition of relative employment growth by 2030 between the Baselines scenario (left, brown) and Electrification scenario (right, blue). The figure illustrates which industries are projected to have net positive and negative employment variations between the two scenarios. It replicates Figure 6 of the main report for 2030, instead of 2050.

**FIGURE A4. RELATIVE EMPLOYMENT VARIATION BETWEEN THE BASELINE (LEFT) AND ELECTRIFICATION (RIGHT) SCENARIOS BY INDUSTRY IN 2030**




**Error! Reference source not found.** complements the aggregate results presented in Figure 8 of the main report. The two graphs show the growth in value added in nine aggregated industry categories and its distribution among wages and profits. As in the main report, the underlying hypothesis is that real wages and functional income distribution (between wages and profits) within each industry remain fixed. Therefore, differences in total functional income distribution, or the value-added growth between the scenarios, depend on the industry composition. In other words, if industries that are more labor-intensive or pay higher wages grow relatively more in one scenario, the wage-share in value-added will increase more in this scenario.

### FIGURE A5. DISTRIBUTION OF VALUE ADDED BETWEEN WAGES AND PROFITS BY INDUSTRY IN 2050 IN THE BASELINE (LEFT) AND ELECTRIFICATION (RIGHT) SCENARIOS



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