Why Does Oil Matter? Commuting and Aggregate Fluctuations*

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Abstract

Oil price shocks are known to have a sizable macroeconomic impact, despite a relatively small fraction of total expenditures that is devoted to energy. Using micro data we document a significant effect of oil prices on labor supply and commuting distance, especially among low-skilled workers who face large commuting costs, relative to their wages. In addition, equity returns of firms in less skill-intensive industries are more sensitive to oil price fluctuations. Motivated by this empirical evidence, we employ a two-sector endogenous growth model with an oil-dependent commuting friction to examine the effect of oil shocks on employment, real wages, and growth, as well as equity prices. Negative oil supply shocks followed by oil price increases depress labor supply, especially in the less capital-intensive low-skill sector, where employment is most sensitive to the cost of commuting. As a result, output growth slows down in the medium run as innovation and capital are reallocated towards the less affected high-skill sector, resulting in subsequent rise in the skill premium. The model also captures key elements of sector-specific demand-driven shocks to oil markets, such as the COVID-19 lockdowns in the spring of 2020.

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1 Introduction

Oil has long held a special place in global commodity markets, as its price fluctuations appear to have outsize consequences for macroeconomic activity. Standard models featuring oil as an input into production struggle to explain the sizable and persistent effect of oil supply shocks on economic growth, since oil-related expenditures constitute only about 3% of GDP. Yet, as pointed out by Bodenstein, Guerrieri and Kilian (2012) and Ready (2018), household oil consumption amounts to about 65% of total oil consumed in the US after 1986, most of it used in transportation. According to Census survey data, 86% of all U.S. workers commute to work by automobile, with 16% of households' income spent on transportation expenditures (approximately one-third of it directly on gasoline - e.g. Redding and Turner (2014)). What is the role of oil prices in driving commuting costs for workers? Is it large enough to affect aggregate economic fluctuations by influencing labor supply?

We begin by documenting several stylized facts on the relation between labor supply, commuting, and oil prices using disaggregated data. Since workers in areas with low population density tend to have longer-distance commutes (and are more likely to commute by car), they are more likely to be sensitive to fluctuations in the cost of commuting that are caused by oil price changes. Similarly, the cost of gasoline can be relatively small for high-skill workers as it constitutes a much smaller fraction of their expenditure than it does for less-skilled, lower-income workers. Using household-level data from the American Community Survey we show that hours worked are indeed negatively related to changes in oil prices. Importantly, this is especially true for lower-skill, lower-paid workers, and for those living in low-density areas (where driving distances are longer). In addition, we use novel data from the U.S. Census, the Longitudinal Employer-Household Dynamics Origin-Destination Statistics (LODES), to show that the average commuting distance increases following positive labor demand shocks, but shrinks following oil price rises, especially for the lower-wage workers, consistent with the idea that gasoline prices are a major component of commuting costs. Finally, we provide evidence from asset prices that low-skill industries are more impacted by high oil prices. We use the labor skill-sorted portfolios of Belo, Li, Lin and Zhao (2017) and show that there is a strong monotonic relationship between industry's average skill level and equity return exposure to oil prices. Low-skill industries have highly significant negative exposure to oil price changes, while high-skill industries have insignificant exposure. This, again, suggests that the heterogeneous response of labor supply across skill levels is an important channel for the propagation of oil price shocks throughout the economy.

In order to better understand the connection between oil supply and the macroeconomy through this commuting cost channel, we propose a general equilibrium model with endogenous productivity growth, building upon models of technological change over the business cycle as in Romer (1990), Comin and Gertler (2006) and, in particular, Kung and Schmid (2015). We incorporate the oil sector through a commuting friction, whereby increasing labor supply requires progressively longer-distance commutes, and therefore a larger amount of oil. Negative correlation between the household income and the part of income spent on transportation suggests that introducing heterogeneity in the labor elasticity to oil shocks is important for explaining sectoral differences in responses to oil shocks. Thus, our model features two sectors that differ primarily in their skill- and capital intensity, which we interpret as sectors hiring either high-skilled or low-skilled workers, similarly to Kopytov, Roussanov and Taschereau-Dumouchel (2018).

Since low-skilled workers are more sensitive to oil price fluctuation than high-skilled workers, we would expect the low-skill sector to suffer more from a negative oil shock as workers are more likely to give up on low-paid jobs, especially when they are required to commute further distances. In fact, our model's prediction that high-skilled workers both supply more labor (as a fraction of total hours) and commute longer distances on average is consistent with our micro data from the ACS, at least qualitatively. In the model, a negative oil supply shock that raises oil prices decreases labor supply disproportionately more in the low-skill sector, while simultaneously increasing the wage skill premium in a persistent fashion, as R&D activity is reallocated to the high-skill sector, boosting its labor productivity further. This response is consistent with the earlier findings of Kaene and Prasad (1996), who show empirically that oil price shocks induce substantial changes in the employment shares and relative wages across industries.

Our model implies that negative oil shocks have a detrimental effect on both sectors in the short run, but since the high-skill sector is less effected, R&D (as well as capital) investment is redirected toward it, resulting in a long-lasting divergence in the relative productivity growth rates over the medium-run. The high-skill sector is hit less than the low-skill sector, and the corresponding real wage skill premium increases in the medium-run. This prediction is in contrast to models of energy-skill complementarity in production, e.g. Kehrig and Ziebarth (2017). Yet it turns out to be consistent with the positive comovement between the oil share of household expenditures and the wage skill premium observed in the recent decades. In addition, model simulations exhibit a large response in labor and little response in aggregate capital, which corresponds well to what is observed in the data as documented in Barsky and Kilian (2004) and Ready (2018), a feature that is difficult to replicate using a standard (e.g., real business cycle-type) model.

Our model can be used to study the evolution of oil prices together with aggregate economic fluctuations in a variety of contexts. In particular, we provide an exercise that captures some of the key elements of the COVID-19 lockdowns in March-April of 2020, whereby low-skill sector of the economy that relies most on physical presence and interaction was severely restricted in its ability to function, causing not only a sharp contraction in output and consumption, but also a large drop in the price of oil (due a decline in commuting) and a divergence in valuations of stocks of high- and low-skill sectors, driven in large part by the reallocation of both physical and intangible capital across sectors.

The impact of oil prices on the macro aggregates and economic growth has been extensively studied in the literature. In a series of papers, Hamilton (1983, 2009, 2012) shows that many of the recessions in the United States since World War II had been preceded by dramatic increases in the price of crude petroleum. Kilian (2009) investigates potential sources of the shocks to the real price of oil, attempting to separate oil supply shocks, demand shocks for industrial commodities and demand shocks specific to the crude oil market, and how each of these propagate into the macroeconomic aggregates. Baumeister and Kilian (2016) elaborate on multiple direct and indirect channels through which oil price shocks are transmitted into the economy, which includes supply and demand channels, inter-sectoral reallocation effect, capital uncertainty effect, and the role of monetary policy responses. Bodenstein and Guerrieri (2011) investigate the propagation channel of country-specific oil supply shocks in a two-country DSGE model and find that the macroeconomic implications of oil price fluctuations vary according to their sources. Fukunaga, Hirakata and Sudo (2010) investigate potential sources of the oil price shocks and their sectoral responses. Their main finding is that effects of oil price shocks by industry depend on the source of the shock as well as on industry characteristics. Olson (1988) argues that the oil shocks had a significant indirect impact on observed productivity slowdowns. Fernald (2014) investigates the role of IT-intensity for the relation between the oil sector and global economic boom and bust in the 2000s. We contribute to this literature by proposing and investigating a novel channel - oil-related labor commuting cost - through which the oil market fluctuations can transmit to the real economy. To our knowledge, this type of shock transmission mechanism has not yet been widely studied in the literature.

Our work also contributes to the growing literature on the intersection of asset pricing and labor economics, particularly relating to the heterogeneity across industries in their reliance on highly skilled, versus less skilled, workers, as in Belo, Li, Lin and Zhao (2017), Kilic (2017), Zhang (2019), as well as the geographic differences in the exposure of local factors of production (such as labor) to aggregate shocks - e.g. Tuzel and Zhang (2017). It is also related to the burgeoning literature on the directed technological change, following Acemoglu (2002), and the role of innovation in driving productivity growth, e.g. Kogan, Papanikolaou, Seru and Stoffman (2017).

2 Empirical Evidence

We begin by analyzing micro data from the American Community Survey for the time period 2005-2016, for which it contains some information about commuting in addition to hours worked, income, and demographics. We are interested in understanding how labor supply responds to oil price fluctuations across categories of workers who might be differentially exposed to the price of oil. For higher income, skilled workers the cost of gasoline is relatively trivial compared to low-wage, unskilled workers. Similarly, for workers in high density metropolitan areas with well-developed public transportation oil prices are largely irrelevant to their labor supply choice. We analyze this by regressing hours worked (for employed workers reporting non-zero hours) on lagged (real) oil price and its interactions with variables that capture these differences: wage income, education, and population density, controlling for local area fixed effects.[1]

Table 1 presents the results. High oil prices have a highly statistically significant negative effect on hours worked in all specifications. This is not surprising given the extant macroeconomic evidence, but could be driven by either supply and demand effects (e.g., labor demand by energy-intensive industries). However, interacting the oil price with the socioeconomic status/labor market variables and local population density indicates that, indeed, these effects are concentrated among those for whom commuting costs are most onerous, as all of the interaction terms are positive, and most are highly significant. For example, having a college education (or higher) reduces the effect of oil prices on hours by roughly one third. Similarly, higher income workers experience a much smaller decline in hours. While this result could potentially

[1]The granularity of local area in the ACS is at the level of U.S. Census Public Use Microdata Area (PUMA), a geographic unit containing at least 100,000 people.

be explained by a higher energy-intensity of low-skill jobs, this would contradict the existing evidence, e.g. Kehrig and Ziebarth (2017).

Table 1: Hours Worked and Oil Prices

Linear regression results from regressing hours worked on age, real wage income, sex, education, lagged real oil price, and population density. Consistent PUMA 2000-2010 identifier is used for local fixed effects. Data are from American Community Survey for years 2005-2016. Density variable is constructed for each consistent PUMA 2000-2010. Only observations for employed respondents with positive number of hours worked, traveled time to work and income are used. *Skilled* is a dummy defined as at least 4 years of college. Standard errors (clustered by year) are in the parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.102***	0.102***	0.102***	0.102***	0.102***	0.102***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$WageIncome$	53.7***	62.2***	62.2***	53.7***	62.2***	54.4***
	(3.96)	(1.35)	(1.35)	(3.96)	(1.35)	(4.93)
$Female$	-4.12***	-4.12***	-4.12***	-4.12***	-4.12***	-4.12***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
$Skilled$	1.29***	0.69*	1.29***	1.29***	0.69*	1.02**
	(0.07)	(0.32)	(0.07)	(0.07)	(0.32)	(0.46)
$OilPrice$	-0.017**	-0.013	-0.009	-0.017**	-0.013	-0.018**
	(0.006)	(0.008)	(0.006)	(0.006)	(0.008)	(0.006)
$Wage \times OilPrice$	0.147**			0.147**		0.135
	(0.064)			(0.064)		(0.080)
$Skilled \times OilPrice$		0.010**			0.010**	0.004
		(0.004)			(0.004)	(0.007)
$Density \times OilPrice$			0.222*	0.104	0.125	0.071
			(0.116)	(0.087)	(0.140)	(0.117)
Constant	34.85***	34.61***	34.41***	34.85***	34.61***	34.90***
	(0.424)	(0.555)	(0.476)	(0.425)	(0.556)	(0.481)
Obs	11,526,550	11,526,550	11,526,550	11,526,550	11,526,550	11,526,550
R^2	0.186	0.186	0.186	0.186	0.186	0.186

We next turn to data from the LEHD Origin-Destination Statistics (LODES), available for the years 2002-2015. This dataset contains information on a number of employees residing in a given census block who are commuting to an employer in any census block location.[2] In our analysis we only use data for the state of Minnesota, where the employee location is recorded at the level of individual establishments, which is not the case for other states. While the entire distribution of worker wage earnings is not available, Census provides three employee numbers

[2]Census blocks are the smallest units for all geographic boundaries the Census Bureau tabulates data for, in particular census tracts. They are areas bounded by visible geographic features such as roads, streams, and railroad tracks, as well as non-visible dividers such as property lines, administrative boundaries, etc.

for three wage categories, which we aggregate into two: those earning at most $3,333 per month, and those earning more. For each employer census block we construct the measure of average employee-weighted commuting distance based on employees of wage category k commuting to census block i in year t:

$$DD_t^{i,k} = \frac{1}{NN_t^{i,k}} \sum_{j=1}^{J_t^i} D_j^i N_t^{i,j,k},$$

where D_j^i is the geodesic distance (in miles) between census blocks i and j (we use ArcGIS to compute these based on the census block coordinates provided by U.S. Census), $NN_t^{i,k}$ is the total number of employees of income category k working in location i in year t, J_t^i is the number of census blocks from which employees commute to location i, and $N_t^{i,j,k}$ is the number of employees of category k commuting from census block i to census block j in year t. We exclude from this calculation workers who reside less than one mile or more than 200 miles away from their employer, as they are unlikely to commute to the reported place of employment by car on a daily basis. The former group (about 5-6% of all workers) are likely to walk or use public transportation, bicycle, etc., whereas the latter (around 1-2%) are more likely to work at varying locations different from the formal establishment (e.g., construction subcontractors) or telecommute (especially relevant for highly-skilled workers).

Regressions of average commuting distance on oil price changes and a host of controls, including location fixed effects at the census block level, are reported in table 2 below. These results show that the average employee-weighted commuting distance decreases in the years following oil price rises, but this effect is muted for higher-wage workers, i.e. those earning more than $3,333/month, in the near term (one- and two- year lags of oil price changes). At the same time, this distance increases following increases in labor demand, proxied by the overall employment growth at a given location. These results are consistent with the intuition of the standard model of urban spatial structure developed by Mills (1967) and Muth (1969).[3] These models effectively imply that commuting distance increases in labor demand as marginal workers are attracted to jobs from further away in response to positive productivity shocks, but higher transportation costs imply a shorter commuting distance, all else equal. They also suggest that this channel is more pronounced for the lower-skill, lower-wage workers, for whom commuting costs are larger relative to their wages. Indeed, we can see empirically that average commuting distance is lower for lower-wage workers, consistent with the commuting costs that are proportional to distance being important. Overall, our empirical results motivate our quantitative model developed below.

As a final piece of motivating evidence we examine skill-based stock portfolios of Belo et al. (2017), who sort firms into quintiles based on a measure of labor force skill constructed using the Specific Vocational Preparation index (SVP) from the Dictionary of Occupational Titles

[3]In these "monocentric" models population density endogenously peaks near job locations in a "central business district" and decays as distance from the center increases, as workers trade off proximity and commuting costs against cost of living.

Table 2: Commuting Distance: LODES Data

Table below presents linear regression results from regressing average weighted commuting distance of employees for each triplets of (Census block)x(Income Category)x(Year) (as long as there is at least one person in that income category working on this block in a given year). Data are from LEHD Origin-Destination Statistics (LODES), available for the years 2002-2015 in Minnesota. The income variable is a dummy which takes a value of one for the observations with data for low income employees (low income defined as roughly the bottom two terciles of the income distribution) and zero for observations for high income employees. Population density and employment growth is annual at the county level. Standard errors (clustered by year) are in the parentheses.

	(1)	(2)	(3)	(4)
ΔOilPrice$_{t-1}$	-1.96*	-2.03*	-2.21*	-2.26*
	(1.07)	(0.99)	(1.19)	(1.13)
ΔOilPrice$_{t-2}$	-2.14**	-2.29**	-2.37**	-2.55**
	(0.94)	(0.94)	(0.93)	(0.91)
ΔOilPrice$_{t-3}$		-0.60		-0.80
		(1.73)		(1.92)
income $\leq$ \$3333	-2.05***	-2.01***	-1.90***	-1.87***
	(0.095)	(0.11)	(0.10)	(0.12)
income $\leq$ \$3333 $\times$ ΔOilPrice$_{t-1}$	-0.15	-0.17	-0.089	-0.10
	(0.22)	(0.23)	(0.23)	(0.24)
income $\leq$ \$3333 $\times$ ΔOilPrice$_{t-2}$	-0.77**	-0.82**	-0.70**	-0.74**
	(0.29)	(0.33)	(0.30)	(0.33)
income $\leq$ \$3333 $\times$ ΔOilPrice$_{t-3}$		-0.29		-0.25
		(0.27)		(0.25)
population density$_t$	0.63	0.24	-2.17***	-2.17***
	(3.19)	(3.29)	(0.16)	(0.16)
employment growth$_{t-1}$	3.99**	3.88***	1.75	1.58
	(1.51)	(1.25)	(2.43)	(2.04)
income $\leq$ \$3333 $\times$ employment growth$_{t-1}$	0.030	-0.031	0.62	0.57
	(1.88)	(1.87)	(1.64)	(1.64)
Constant	18.1***	18.4***	20.1***	20.2***
	(2.57)	(2.80)	(0.42)	(0.59)
Observations	853400	853400	853400	853400
Employer blockgroup FE	Yes	Yes	No	No
R^2	0.13	0.13	0.023	0.024

(DOT).[4] While they are focused on the relation between hiring costs and expected returns within these portfolios, we are interested in whether labor skill is related to firms' exposure to oil price changes. Table 3 shows regressions of monthly excess returns on the skill-sorted portfolios on percentage changes in oil prices. Panel A shows the results from univariate regressions and Panel B controls for the CRSP value-weighted market excess return. In both panels we see that rising oil prices are associated with negative returns in low-skill industries, and this effect decays monotonically across the portfolios, so that high-skill industries have insignificant exposure to oil prices.[5] This result provides additional evidence that high oil prices have the strongest negative impact on firms predominantly employing low-skill workers.

3 Model

In this section we introduce our two-sector production-based model with endogenous growth and a novel oil-related commuting friction. The production side of the economy is composed of two semi-final good sectors that utilize different types of labor (either highly-skilled or unskilled), which jointly contribute to the production of the final good used in consumption, investment, and creation of new patented products. The high-skill sector differs from the low-skill sector in that it has both a higher labor productivity and capital intensity, as well as a higher R&D intensity. Each sector's productivity is subject to the endogenous growth in the number of patented products or "blueprints" in the language of Kung and Schmid (2015). In order to illustrate the role of the commuting channel, we assume that oil is used in the economy only by households for commuting purposes and its supply is determined exogenously.

3.1 Household

The representative household derives utility from consumption C_t and amount of leisure over its infinite lifetime. It contains an infinite number of atomistic agents where $\overline{L}^H$ of them are high-skilled (can work in the capital intensive sector) and $\overline{L}^U$ of them are low-skilled (can work in the less capital-intensive sector). Both types of agents can choose leisure that contribute in the same way to the representative household's utility function or work for the corresponding wage. In order to keep the model on the balanced growth path, the leisure input in the utility function is multiplied by the deterministic $Trend_t$ factor. Household has to spend resources on oil for commuting separately for high-skilled and low-skilled workers.

$$\max_{C_t, l_t^H, l_t^U} U_t = \max \left[(1-\beta)\Big(C^{1-\phi}[Trend_t(leisure_t)]^{\phi}\Big)^{1-1/\psi} + \beta\Big(E_t U_{t+1}^{1-\gamma}\Big)^{\frac{1-1/\psi}{1-\gamma}} \right]^{\frac{1}{1-1/\psi}}$$

[4] We thank Jun Li for providing the data.

[5] The fact that some of the industries have a positive exposure to oil prices due to their role in oil extraction and distribution is not driving this result. Industries related to oil extraction primarily reside in the central portfolios (they require roughly average levels of skill).

Table 3: Regressions Skill-based Stock Portfolios on Oil Prices

This table shows regressions of the returns to labor-skill sorted portfolios from Belo, Li, Lin, and Zhao (2017) on changes in oil prices (measured in percent). In Panel A, the independent variable is the percentage change in oil price, and Panel B additionally controls for the aggregate market return. Column (1) - (5) represent returns going from the lowest to highest skill quintile, and Column (6) is the return to a strategy which goes long the highest quintile and short the lowest quintile. Data are from April of 1983 to December of 2014. T-stats are shows in parentheses.

Panel A: Exposure to Oil Price Changes as Independent Variable

	Low Skill (1)	Quintile 2 (2)	Quintile 3 (3)	Quintile 4 (4)	High Skill (5)	HML (skill) (6)
Δp	-0.09***	-0.04	-0.01	0.01	0.02	0.11***
	(-2.80)	(-1.52)	(-0.42)	(0.35)	(0.64)	(4.35)
Constant	0.80***	0.83***	0.72***	0.59***	0.63**	-0.17
	(3.13)	(3.76)	(2.99)	(2.62)	(2.20)	(-0.85)
Observations	380	380	380	380	380	380
R-squared	0.02	0.01	0.00	0.00	0.00	0.05

Panel B: Exposure to Oil Price Changes and Aggregate Market Returns

	Low Skill (1)	Quintile 2 (2)	Quintile 3 (3)	Quintile 4 (4)	High Skill (5)	HML (skill) (6)
Δp	-0.09***	-0.04***	-0.01	0.01	0.02*	0.11***
	(-5.19)	(-3.51)	(-0.92)	(0.96)	(1.89)	(4.49)
Market Return	0.94***	0.87***	0.93***	0.93***	1.17***	0.23***
	(30.24)	(40.15)	(37.20)	(51.48)	(55.19)	(5.11)
Constant	0.20	0.27***	0.13	0.00	-0.12	-0.32
	(1.43)	(2.83)	(1.12)	(0.02)	(-1.27)	(-1.59)
Observations	380	380	380	380	380	380
R-squared	0.71	0.81	0.79	0.88	0.89	0.11

subject to:

$$C_t + P_t^O\left[\Upsilon^H(l_t^H) + \Upsilon^U(l_t^U)\right] = W_t^H l_t^H + W_t^U l_t^U + \widetilde{D}_t \tag{1}$$

$$leisure_t^H + l_t^H = \overline{L}^H \tag{2}$$

$$leisure_t^U + l_t^U = \overline{L}^U \tag{3}$$

$$leisure_t = leisure_t^H + leisure_t^U \tag{4}$$

$$C_t, l_t^H, l_t^U, leisure_t^H, leisure_t^U >= 0$$

where $\Upsilon^j(l_t^j)$ is the quantity of oil required for l_t^j units of labor to be supplied and P_t^O is the price of oil.

The agent's FOC are given by:

$$C_t: \qquad \frac{\partial U_t}{\partial C_t} = \lambda_t$$

$$l_t^j: \qquad -\frac{\partial U_t}{\partial l_t^j} = \lambda_t(W_t^j - P_t^O \Upsilon_t'^j(l_t^j)) \qquad \text{for} \quad j \in \{H, U\}$$

Eliminating Lagrange multiplier for the budget constraint λ_t we get

$$-\frac{\partial U_t}{\partial l_t^j} \Big/ \frac{\partial U_t}{\partial C_t} = W_t^j - P_t^O \Upsilon_t'^j \qquad \text{for} \quad j \in \{H, U\} \tag{5}$$

and the stochastic discount factor (SDF) is

$$m_{t+1} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{-1/\psi - \phi(1-1/\psi)} \left(\frac{Trend_{t+1}(leisure_{t+1})}{Trend_t(leisure_t)}\right)^{\phi(1-1/\psi)} \left(\frac{U_{t+1}}{E_t[U_{t+1}^{1-\gamma}]^{\frac{1}{1-\gamma}}}\right)^{1/\psi - \gamma}. \tag{6}$$

We assume that households are the stock owners and thus they receive the aggregate dividend denoted by $\widetilde{D_t}$. It includes the net payout from the production sector (final good firm dividend D_t and profits of innovation sector). Additionally, we assume that they also receive the lump sump transfer of rents from the sales of oil (the assumption of domestic ownership of oil resources does not materially effect our results, however). Thus we can specify its components as:

$$\widetilde{D_t} = D_t + \int_0^{N_t^H} \pi_{i,t}^H + \int_0^{N_t^U} \pi_{i,t}^U + t_t P_t^O \tag{7}$$

However household does not internalize those components when making their optimal decisions about consumption and labor taking the dividend stream $\widetilde{D_t}$ as given.

Commuting friction

We assume exponential form for the $\Upsilon(.)$ function:

$$\Upsilon^j(l) = l^\kappa.$$

Thus, total commuting cost for a given type of workers is increasing and convex in the amount of hours worked. In our baseline parametrization, we assume that the $\Upsilon(.)$ function is the same for both labor types. This convex shape of the commuting cost can be micro-founded using a version of the Mills-Muth model of urban structure. Intuitively, it reflects the fact that the population density of workers around a city center (where most of the jobs are located) is decreasing with the radius. Given perfect risk sharing, only workers living closest to the city center provide work first, so that increasing labor supply requires that workers living further away from the center being engaged and therefore the marginal commuting distance increases with each extra worker employed.

3.2 Production

The final good Y_t is produced using two semi-final goods, Y_t^H and Y_t^U, each being produced using either more or less capital-intensive technology. The semi-final good technologies are subject to the endogenous growth in the measure of patented products denoted with N_t^H and N_t^U similarly to Kung and Schmid (2015). Sustained growth arises endogenously from the development of new patented products but is "directed" towards the two sectors at different rates, reflecting expected profitability of each sector.

3.2.1 Final good sector

The final good sector chooses levels and input factors so as to maximize the shareholder value. Physical capital investment are subject to the convex capital adjustment cost as in Jermann (1998). The firm chooses the optimal level of labor l_t^H and l_t^U, capital K_t^H and K_t^U, and the quantity of intangible intermediate input $x_{i,t}^j$ contributed by each of the patented products $i \in [0, N_t^j]$, purchased at a price $p_{i,t}^j$. Investment in the physical capital I_t^H and I_t^U is subject to the convex capital adjustment cost, and capital is sector-specific, i.e. it cannot be reallocated between the skilled and unskilled technologies.

The final-good producer thus solves

$$\max_{\{I_{t+j}^H, I_{t+j}^U, K_{t+1+j}^H, K_{t+1+j}^L, l_{t+j}^H, l_{t+j}^U, x_{ih,t+j}^H, x_{iu,t+j}^U\}_{j\geq 0, ih\in[0,N_t^H], iu\in[0,N_t^U]}} E_t \sum_{j=0}^{\infty} m_{t+j} D_{t+j}$$

subject to:

$$D_t = Y_t - W_t^H l_t^H - W_t^U l_t^U - I_t^H - I_t^U - \int_0^{N_t^H} p_{i,t}^H x_{i,t}^H di - \int_0^{N_t^U} p_{i,t}^U x_{i,t}^U di$$

$$K_{t+1}^H = (1-\delta) K_t^H + \Phi_t\big(I_t^H / K_t^H\big) K_t^H \tag{8}$$

$$K_{t+1}^U = (1-\delta) K_t^U + \Phi_t\big(I_t^U / K_t^U\big) KU_t \tag{9}$$

$$Y_t = \Big(\big(Y_t^U\big)^{\iota} + \mu \big(Y_t^H\big)^{\iota} \Big)^{\frac{1}{\iota}} \tag{10}$$

$$Y_t^j = \Big[(K_t^j)^{\alpha^j} (a_t^j l_t^j)^{1-\alpha^j} \Big]^{1-\xi^j} (G_t^j)^{\xi^j} \quad \text{for} \quad j \in \{H, U\} \tag{11}$$

$$G_t^j = \left[\int_0^{N_t^j} (x_{i,t}^j)^{\nu^j} di \right]^{\frac{1}{\nu^j}} \quad \text{for} \quad j \in \{H, U\} \tag{12}$$

$$\Phi_t^j \left(\frac{I_t^j}{K_t^j} \right) = \frac{a_1}{1 - 1/\zeta} \left(\frac{I_t^j}{K_t^j} \right)^{1-1/\zeta} + a_2 \quad \text{for} \quad j \in \{H, U\} \tag{13}$$

FOC are:

$$I_t^H : \qquad Q_t^H = \frac{1}{\Phi_t'^H} \tag{14}$$

$$I_t^U : \qquad Q_t^U = \frac{1}{\Phi_t'^U} \tag{15}$$

$$K_{t+1}^H : \qquad Q_t^H = E_t \bigg[m_{t+1} \bigg(Q_{t+1}^H (1 - \delta) - \frac{I_{t+1}^H}{K_{t+1}^H} + Q_{t+1}^H \Phi_{t+1}^H + MPK_{t+1}^H \bigg) \bigg] \tag{16}$$

$$K_{t+1}^U : \qquad Q_t^U = E_t \bigg[m_{t+1} \bigg(Q_{t+1}^U (1 - \delta) - \frac{I_{t+1}^U}{K_{t+1}^U} + Q_{t+1}^U \Phi_{t+1}^U + MPK_{t+1}^U \bigg) \bigg] \tag{17}$$

$$l_t^j : \qquad MPL_t^j = W_t^j \quad \text{for} \quad j \in \{H, U\} \tag{18}$$

$$x_{i,t}^j : \qquad p_{i,t}^j = \frac{\partial Y_t}{\partial Y_t^j} \Big[(K_t^j)^{\alpha^j} (a_t^j l_t^j)^{1-\alpha^j} \Big]^{1-\xi^j} \xi^j \left[\int_0^{N_t^j} (x_{i,t}^j)^{\nu^j} \right]^{\frac{\xi^j}{\nu^j} - 1} (x_{i,t}^j)^{\nu^j - 1} \quad \text{for} \quad j \in \{H, U\} \tag{19}$$

Note that final good sector take the composite G_t^j factor as exogeneous.

3.2.2 Intermediate products sectors

Innovation occurs through development of intermediate good varieties, whereby each variety represents a patented product that is imperfectly substitutable in the production of a semi-final good. Products are "developed" by competitive innovators and "sold" in the form of (perpetual) patents to intermediate goods producers, who then produce the actual intermediates based on these patents and are monopolistically competitive (since each is a monopolist in a given variety). There are two separate directions of innovation, one contributing to the capital-intensive technology H and the other one contributing to the non-capital-intensive technology U. Thus the specification below applies to each of them separately.

Intermediate (intangible) good sector (monopolistic competition)

Intermediate good producers solve the following static profit maximization problem each period:

$$\pi^j_{i,t} = \max_{p^j_{i,t}} (p^j_{i,t} - 1) x^j_{i,t}(p^j_{i,t}) \quad \text{for} \quad j \in \{H, U\}.$$

As noted by Kung and Schmidt (2015), the monopolistically competitive characterization of the intermediate goods sector a-la Dixit and Stiglitz (1997) results in the symmetric industry equilibrium conditions, thus we have:

$$x^j_{i,t} = x^j_t \qquad \text{for} \quad j \in \{H, U\}$$

$$p^j_{i,t} = p^j_t = \frac{1}{\nu^j} \qquad \text{for} \quad j \in \{H, U\} \tag{20}$$

Combining it with 19, 12 we get:

$$\pi^j_{i,t} = \pi^j_t = \left(\frac{1}{\nu^j} - 1\right) x^j_t \qquad \text{for} \quad j \in \{H, U\}$$

$$x^j_t = \left(\frac{\partial Y_t}{\partial Y^j_t} \xi^j \nu^j \left[(K^j_t)^{\alpha^j} (a^j_t l^j_t)^{1-\alpha^j}\right]^{1-\xi^j} (N^j_t)^{\frac{\xi^j}{\nu^j} - 1}\right)^{\frac{1}{1-\xi^j}} \qquad \text{for} \quad j \in \{H, U\} \tag{21}$$

Innovation sector (perfect competition)
The innovation sector develops patented products and sells them at a price equal to the value of the patent to the intermediate good producer, $v_{j,i,t}$

$$v^j_{i,t} = \pi^j_{i,t} + (1 - \tau^j) E_t[m_{t+1} v^j_{i,t+1}] \qquad \text{for} \quad j \in \{H, U\} \tag{22}$$

where τ^j is the probability that a patent becomes obsolete.

Evolution of the number of patented products N^j_t

$$N^j_{t+1} = \vartheta^j_t S^j_t + (1 - \tau^j) N^j_t \qquad \text{for} \quad j \in \{H, U\}, \tag{23}$$

with

$$\vartheta^j_t = \frac{\chi^j N^j_t}{(S^j_t)^{1-\eta} (N^j_t)^{\eta}} \qquad \text{for} \quad j \in \{H, U\}, \tag{24}$$

where ϑ^j_t represents the productivity of the innovation sector and is meant to capture decreasing returns to scale in aggregate innovation (i.e., a form of the congestion externality).

Since discounted future profits on patents are the payoff to innovation and the patented products sector is competitive, the optimality condition that pins down the number of new patented products S^j_t is:

$$E_t[m_{t+1} v^j_{t+1}](N^j_{t+1} - (1 - \tau) N^j_t) = S^j_t \qquad \text{for} \quad j \in \{H, U\}. \tag{25}$$

Market clearing

Market clearing conditions for consumption goods and oil are given by

$$Y_t = C_t + I_t^H + I_t^U + N_t^H x_t^H + N_t^U x_t^U + S_t^U + S_t^H \tag{26}$$

and

$$t_t = \Upsilon_t^H(l_t^H) + \Upsilon_t^U(l_t^U), \tag{27}$$

respectively.

Technology processes and oil supply

Both skilled and unskilled technologies are subject to exogenous transitory productivity shocks

$$log a_t^U = \rho^A log(a_{t-1}^U) + \sigma^A \epsilon_t^U, \tag{28}$$

$$log a_t^H = log(\widetilde{a})(1-\rho^A) + \rho^A log(a_{t-1}^H) + \sigma^A \epsilon_t^H,$$

and

$$log t_t = log(t_{ss})(1-\rho^T) + \rho^T log(t_{t-1}) + \sigma^T \epsilon_t^t. \tag{29}$$

3.3 Implications

Endogenous growth

Plugging (21) into the production function we get that output in semi-final good sector is given by:

$$Y_t^j = (K_t^j)^{\alpha^j}(a_t^j l_t^j)^{1-\alpha^j}\left(\frac{\partial Y_t}{\partial Y_t^j}\xi^j\nu^j\right)^{\frac{\xi^j}{1-\xi^j}}(N_t^j)^{\frac{\frac{\xi^j}{\nu^j}-\xi^j}{1-\xi^j}} \qquad \text{for} \quad j \in \{H, U\}.$$

If we impose $\frac{\frac{\xi^j}{\nu^j}-\xi^j}{1-\xi^j} = (1-\alpha^j)$, as required for the balanced growth, we can embed the augmented endogenous TFP shock Z_t^j as follows

$$Y_t^j = (K_t^j)^{\alpha^j}(Z_t^j l_t^j)^{1-\alpha^j} \qquad \text{for} \quad j \in \{H, U\}$$

where

$$Z_t^j = \left(\frac{\partial Y_t}{\partial Y_t^j}\xi^j\nu^j\right)^{\frac{\xi^j}{(1-\xi^j)(1-\alpha^j)}} a_t^j N_t^j \qquad \text{for} \quad j \in \{H, U\}.$$

Thus, "measured" total factor productivity in each sector endogenously follows allocation of R&D expenditures in the given sector.

High-skill wage premium

Note that since the marginal utility of leisure (marginal disutility from labor) for both high-skilled and unskilled workers is the same, effectively we must have:

$$W_t^U - P_t^O \Upsilon_t'^U = W_t^H - P_t^O \Upsilon_t'^H$$

or the wage premium must be

$$W_t^H - W_t^U = P_t^O \Big(\Upsilon_t'^H(l_t^H) - \Upsilon_t'^U(l_t^U) \Big). \tag{30}$$

Thus, the larger is the skill premium, the more high-skilled labor is supplied relative to unskilled labor. This implies that skilled workers require more oil expenditure on average as they travel more miles on average, since the marginal skilled worker is located further away from the job relative to the unskilled worker. The magnitudes of these differences are proportional to the skill premium: the higher is the pay differential, the larger is the disparity in the labor supply, as it compensates for a larger difference in commuting costs.

Importantly, this prediction is at least qualitatively corroborated in the ACS data. Figure 1 displays summary statistics of commute times and hours worked by skill level (defined either as hourly wage quintile, or by level of education). In all cases the distributions are both centered further to the right and more right-skewed for higher skilled workers: they both supply more hours and commute further to work.

4 Analyzing the Effects of Oil Shocks: Model vs. Data

We use the model to explore the behavior of key macroeconomic variables in response to a negative oil supply shock. We calibrate the model to quantitatively match the standard features of the aggregate U.S. economy; means and standard deviations of target moments are reported in Table 5 and Table 6, respectively; calibrated parameter values are presented in Table 4. Most of the parameters are as in the Kung and Schmid (2015) and they are calibrated using simulations at a quarterly frequency. Leisure preference ϕ and commuting friction parameter κ are calibrated to match oil-related moments in the data, such as oil price volatility and the share of oil in consumption (note that while the model matches the higher end of the values in the data, where consumption of goods is used in denominator, it substantially overshoots the lower value that uses total household consumption expenditures, e.g. from the Consumer Expenditure Survey). Sectoral capital shares α^H and α^U together match the total capital share in the economy. R&D productivity scale parameters χ^U and χ^H are calibrated to match growth rates in both sectors to the imposed endogenous growth rate of the economy.

4.1 Impulse Responses

Figure 2 confirms the commonly accepted belief that the oil supply shock has a detrimental effect on the economy. The mechanism through which it works in our model is as follows: the

Figure 1: Commuting and labor supply by skill level: ACS

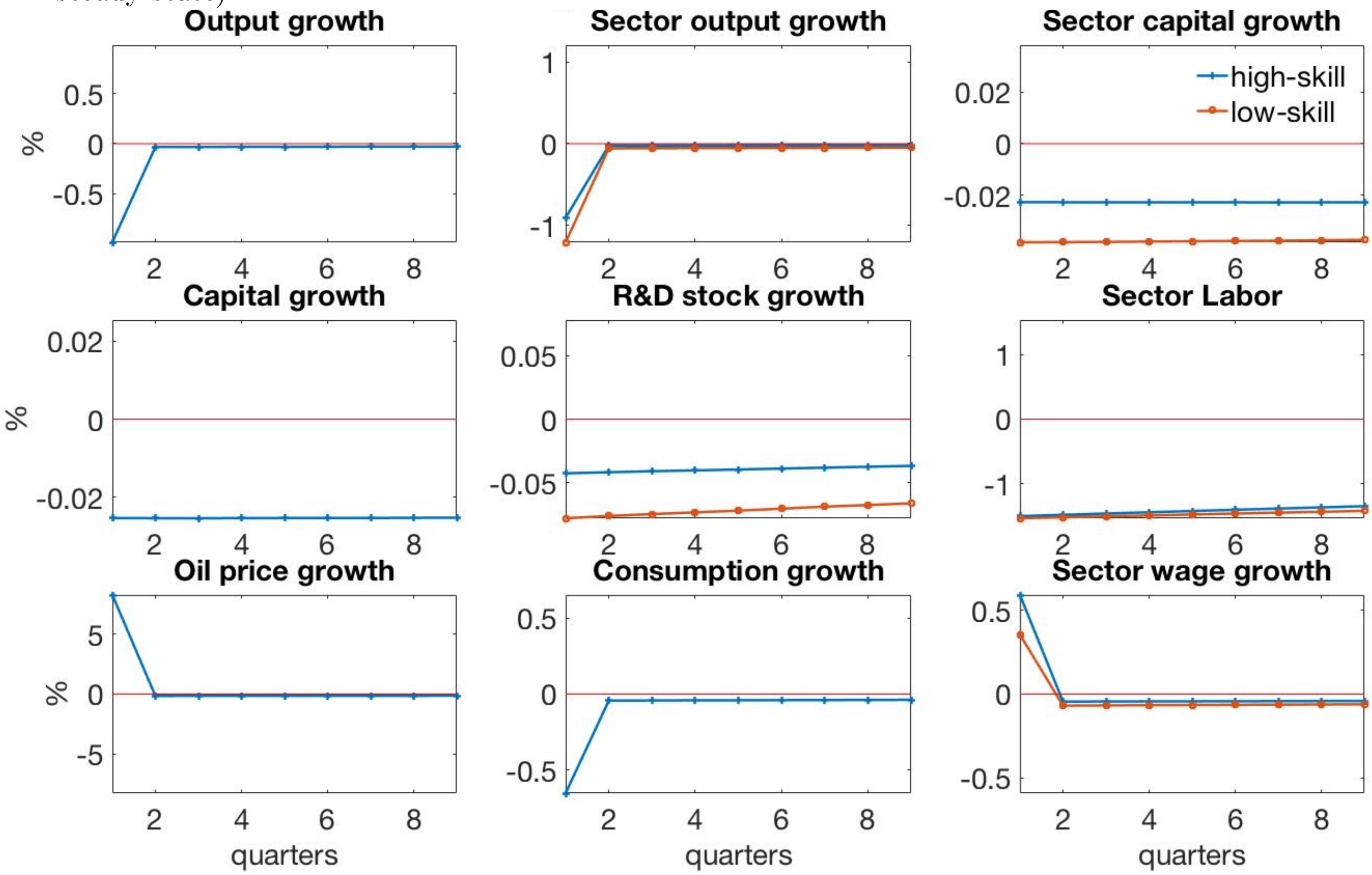
The box plots illustrate the distributions of travel time to work (top panels) and usual hours worked (bottom panels) across different income and education categories using 2016 American Community Survey. Hourly wage quintiles are ordered from the lowest to the highest (left two panels). Workers having at least college degree are defined as "skilled" (right two panels). Each colored box includes the second and third quartiles of the distribution. Whiskers indicate 1.5 inter-quartile range distances above the 75th percentile and below 25th percentile. Means values are denoted with circles and medians with horizontal dividers. Travel time to work is expressed in minutes and refers to minutes spent to travel from home to work.

decreased oil supply causes a hike in the price of oil.[6] Thus it is more costly for workers to commute to work, which makes them work less and require a higher wage. Companies facing the lower amount of labor employed decrease their investment in physical capital and demand for intangible goods. Because of the lower demand for the intangible goods, the value of new patents decreases and thus the R&D investments decrease. All of this has a detrimental effect on the economy, causing a decrease in output and consumption growth.

The two sectors respond differently, however. The relative strength of the inter-sectoral responses is presented on Figure 4.1. We can see that after the negative oil supply shock, the relative size of sectoral output, number of patented products, wages, capital, and labor are generally shifting in favor of the high-skilled sector. This suggests that the high-skill sector

[6]We focus here on oil supply shocks in order to isolate the exogenous effect of oil prices on the economy. Impulse responses of the economic quantities to the sectoral labor productivity shocks are relatively standard, where a positive shock to a particular sector increases its output, wages, labor demand, capital, etc.; both sectors' shocks that increase labor demand also increase the price of oil. Detailed impulse response function plots are provided in the Appendix.

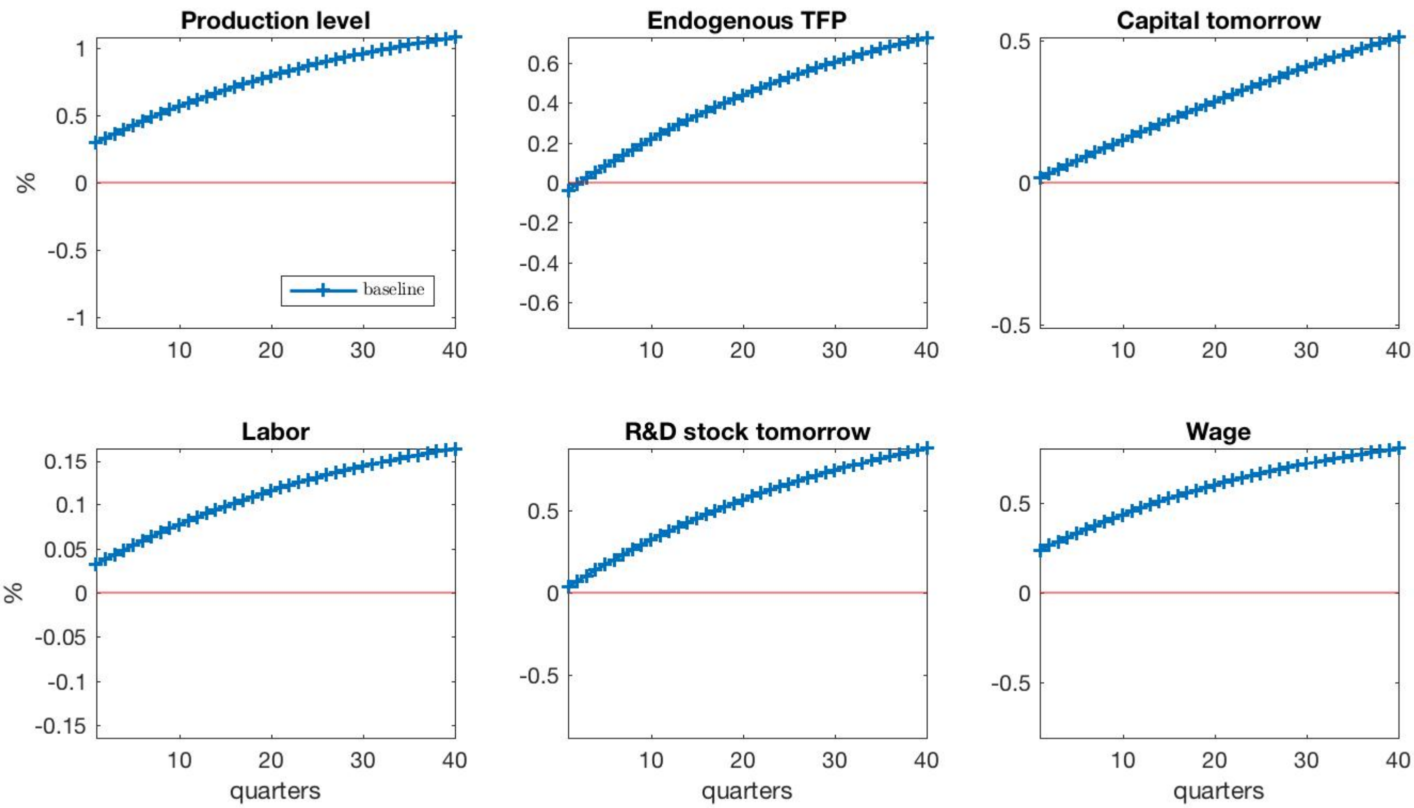
Figure 2: Oil shock implications for growth. IRF to negative oil supply shock (deviation from the steady state).



suffers less than the low-skilled sector in the event of an oil price spike. Interestingly, the augmented TFP in the high-skill sector decreases at a faster pace than in the low-skilled sector during the few first periods, causing the ratio of the augmented TFP in the high-skill sector to low-skill sector to decrease initially. This is due to the immediate shift in capital and innovative activity towards the high-skill sector, which, due to the law of decreasing returns to scale causes the observed immediate drop in the relative augmented TFP. However, due to the relatively small decrease in intangible investment in the high-skill sector, in the long term its productivity does relatively better than the low-skill sector (compared to the steady state levels).

An interesting consequence of an oil shock in our model is its effect on the wage skill premium. The impulse responses show that it widens on impact of a negative oil supply shock, and continues to widen going forward. This might appear surprising, since low skill labor supply is more impacted by the shock. However, it is precisely the difference in the sensitivities of the two groups that drives this result: since high-skilled labor supply is less elastic, high-skilled workers' wages rise more than low-skilled ones'. Indeed, recall that the wage premium is given

Figure 3: Relative IRF between high and low skilled sectors to negative oil supply shock (followed by oil price increase).



Note: Ratio between IRFs for high-skill sector to low-skill sector, ie K_t^H/K_t^U. Since R&D stock and Capital are pre-determined variables quarter t response on the graph corresponds to quarter t+1 in the model. The numbers correspond to 100*log-deviation from the steady state. Thus for small numbers they are approximately equal to the percentage deviations.

by

$$W_t^H - W_t^U = P_t^O \Big(\Upsilon_t'^H(l_t^H) - \Upsilon_t'^U(l_t^U) \Big).$$

As oil price increases, the term in the parentheses does too, since $l_t^H > l_t^U$, and unskilled labor decreases by more than skilled, so that the slope of $\Upsilon_t'^H(l_t^H)$, even though steeper, decreases less than that of $\Upsilon_t'^U(l_t^U)$. Thus, the skill premium rises on impact. It continues to rise in the medium term because investment and the R&D activity, while lower overall, now favor the high-skilled industry, raising its demand for labor in the future. Thus the asymmetry in sectoral responses to the oil shock in our model can be seen as a novel force behind skill-biased technological change.

4.2 Empirical VAR

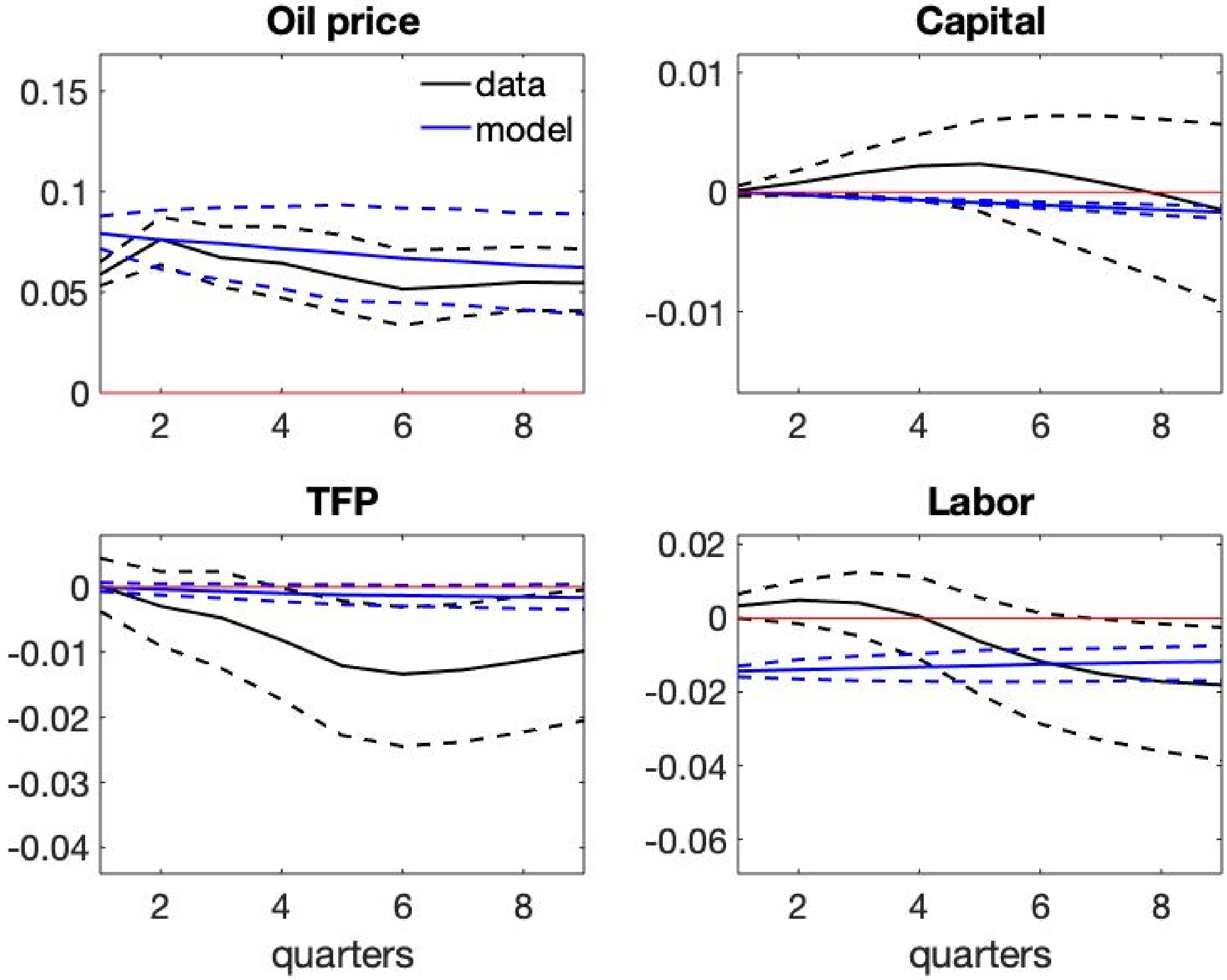
To bring our model results closer to the data, we estimate a VAR for aggregate ouput and its most commonly identified components, namely capital and labor input, and total factor productivity (TFP). Figure 4 presents the impulse responses for one standard deviation of the positive shock in oil price equation from the VAR model. Empirical impulse response functions are based on estimates in Ready (2018), while model counterparts are computed using simulations obtained from the baseline parametrization. Total labor in the economy is simply the sum of labor employed in high- and low-skill sectors. Total factor productivity is estimated as Solow residuals. We obtained an estimate for the capital share parameter alpha of 0.33, which is in line with the previous literature. We can see that the impulse responses for the time series simulated in the model match the magnitude of the oil price response observed in the data. We can also see that the model was able to replicate the negative response in the TFP, however with smaller magnitude. The response in capital is negative, but very small in magnitude (close to zero) and thus corresponds well to what is observed in the data. Last but not least, the labor response matches the data relatively well in terms of the direction and magnitude. While in the model the response of labor is instantaneous, whereas in the data it is delayed, presumably due to various labor market frictions that we do not model, the long-run impact in the data is very similar to that produced in the model.

4.3 Oil Prices and the Wage Skill Premium

One of the key predictions of the model is that the wage skill premium will be closely related to the cost of commuting, and hence fuel costs, which are primarily driven by oil prices. We find that this prediction is strongly supported in the data. Figure 5 plots the ratio of total household expenditure on gasoline, which tracks oil prices insofar they are relevant for the consumers, against the growth in wages for high- relative to low-wage workers. The relative wage growth is constructed using the Atlanta Fed's Wage Growth Tracker, and compares the wage growth for workers in the top quintile of wages vs those in the bottom. The ratio of household expenditure is from the consumer expenditure survey, and closely tracks the real price of oil. Panel A shows this plot for the period for which the Wage Growth Tracker has data, namely 1998 to 2018. As the plot shows the two series largely move together, with the notable exception of the technology bubble of the early 2000s, a period that likely saw a productivity shock specifically for high-wage workers.

Panel B plots the portion of Panel A since the financial crisis, a period that has seen large variation in oil prices but steady overall economic growth. As the plot shows, the high oil prices following the immediate recovery from the Great Recession corresponded with a period of relatively lackluster wage growth for low-wage jobs. In contrast, since 2015 with the fall in oil prices coming from North American Shale Oil boom, these wages have grown considerably

Figure 4: Response of Components of Output to Change in Oil Price and 98% CI



Note: Using VAR(4) model on first differences. Data part based on Ready (2012). Model part estimated using simulations obtained from baseline model. Economy-wide TFP from the model estimated using Solow residuals. Estimated alpha = 0.375 (using simulations from the model).

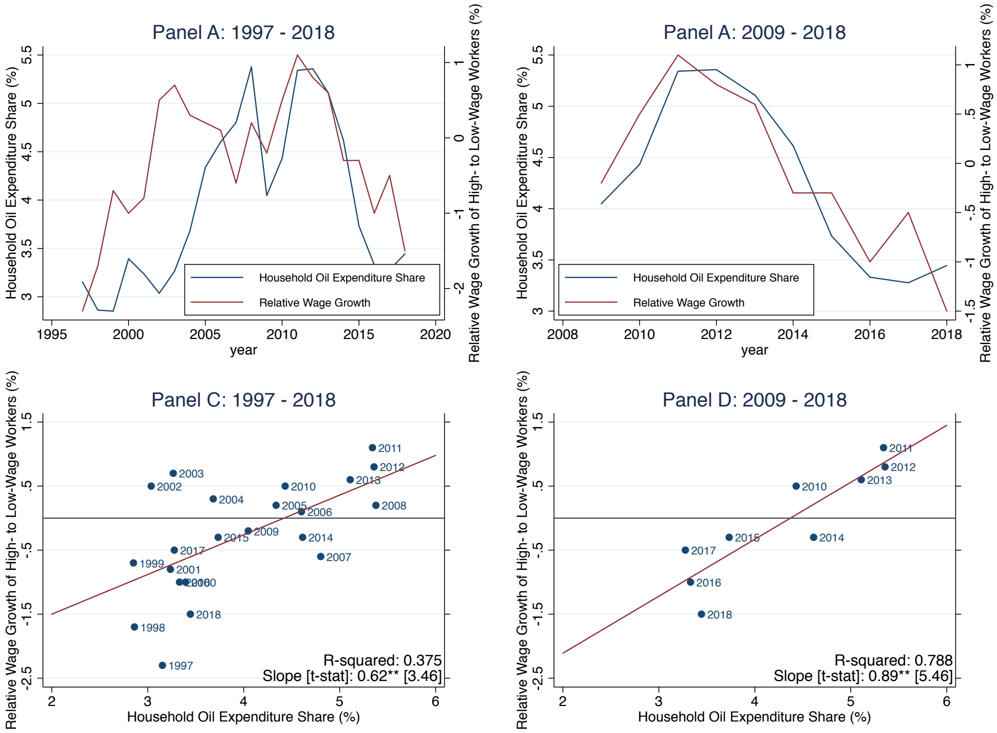
faster than those for high-wage workers.[7] Panels C and D use the same data for plots A and B but show the two lines in scatter plot form with OLS regressions. As the plot shows, for both periods, and particularly for the second, the level of household oil expenditure closely relates to the change in the wage skill premium. This evidence strongly supports our model's prediction that, at least in the recent era, oil price fluctuations have a stronger negative effect on the wages of lower-skilled than high-skilled workers.

4.4 COVID-19 Lockdowns

We perform an additional exercise that helps illustrate the model's empirical relevance. We consider events surrounding the onset of the COVID-19 crisis in the U.S. in 2020 and the impact

[7] Gilje, Ready and Roussanov (2016) quantify the role of oil supply shocks during this time period.

Figure 5: Oil Expenditures and the Wage Skill Premium



The figure shows plots of household share of consumption and the relative wage growth of high- and low-wage workers. Household share of consumption is defined as the ratio of expenditure on gasoline and other energy goods to total consumption expenditure for all workers in the bureau of labor statistics consumer expenditure survey. Relative wage growth is defined as the difference in wage growth between workers in the highest quartile of wages and the lowest quartile of wages and is obtained from the Federal Reserve Bank of Atlanta's Wage Growth Tracker. Panels C and D use the same data as Panel A and B, but present regression scatter plots. The t-stats in these panels are calculated using Newey-West errors with 3 lags.

it had on labor markets, whereby most public business activity was subject to either official lock-down orders or voluntary reduction of in-person economic activity of economic agents. This crisis had a bifurcated impact on labor markets, whereby high-skill (cognitive) workers largely shifted to working from home (e.g., telecommuting) as a substitute to commuting to work but generally continued to supply labor, where as a large number of unskilled (manual) workers were forced to stop supplying labor due to shut-downs of businesses requiring physical presence, many facing unemployment or furloughs. We model this situation as a large negative (and transitory) productivity shock to the unskilled-labor technology, while leaving the skilled-labor technology unaffected (while this is clearly a simplification, it is meant to capture the fact that productivity losses due to working from home are small compared to shut-downs of entire establishments, such as restaurants, etc.)

Figure 6 plots the impulse response functions as deviations of log variables from steady state after a negative shock to low skill labor productivity. Due to the local approximation nature of the perturbation methods used to solve the model, the IRFs are computed for the shock to productivity equal in magnitude to the standard deviation of its innovations. Naturally the magnitude of the shock that would correspond to the COVID-19 lockdown in March of 2020 would be much bigger, however we believe the directional responses and their relative magnitudes can still be informative. The drop in total aggregate output and consumption comes entirely from the fall in the unskilled-sector while the high-skilled-sector output is fairly unaffected. Similarly the investment in both physical and intangible capital dropped significantly in the low-skill sector while in the high-skill sector experienced even a slight increase in investments. As the R&D stocks drive endogenous long-term growth rates in both sectors, this divergence of the investments between sector will be felt for long time in form of lower growth in the low-skill sector. Aggregate consumption growth falls by roughly same magnitude as the aggregate output. While unskilled labor supply falls sharply and continues to fall over the following quarters as investment shifts to the skilled sector, in the latter labor actually increases, and continues to drift upwards. Wages drop in both sectors, albeit much more so in the unskilled sector than the high-skill one. Moreover, the low skill wages continue to growth at the lower rate than high-skill in the next quarters.

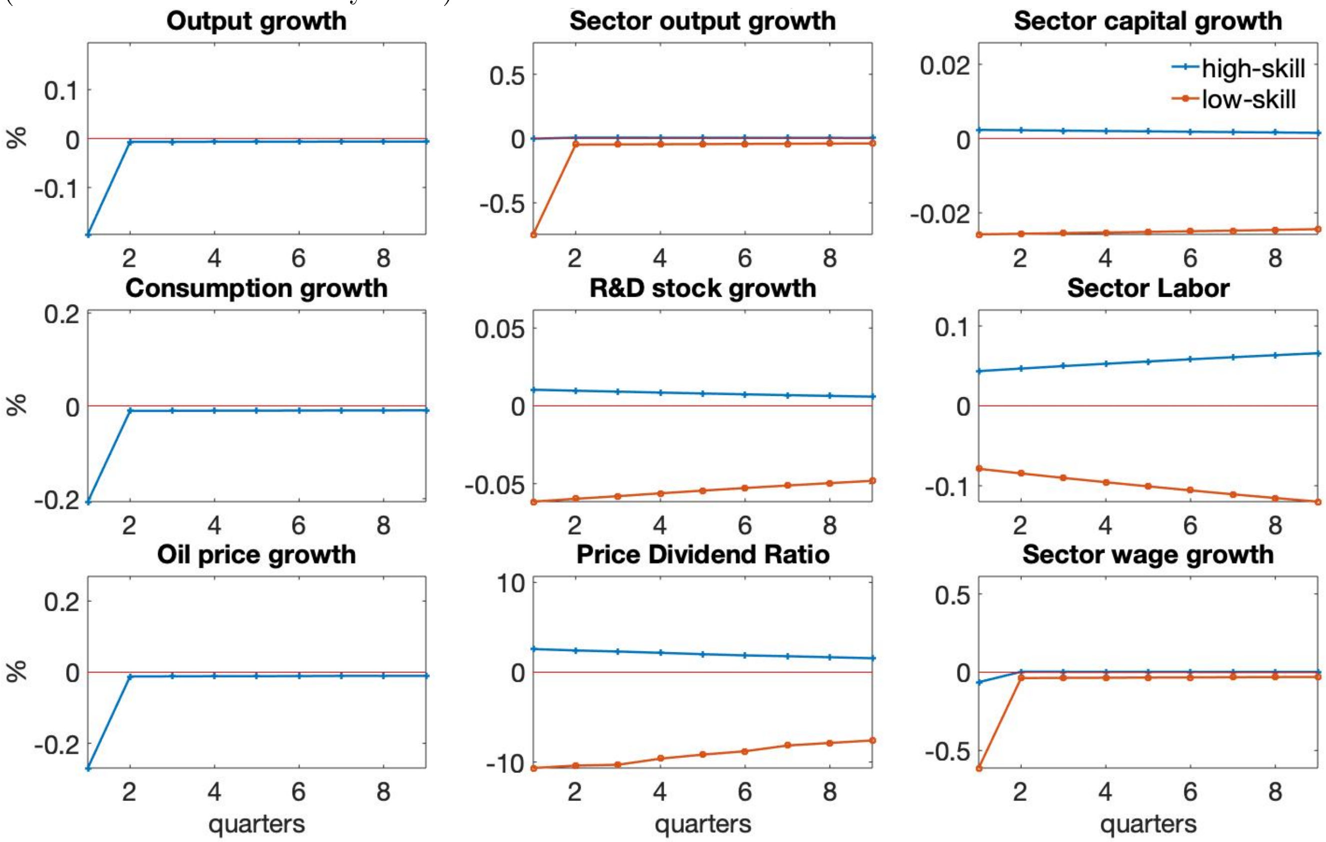
Oil prices, which are central to our analysis, drop precipitously on impact, experiencing a somewhat larger percentage-point drop than output.[8] While oil prices fell even more sharply in the data, note that our approach provides a lower bound on the magnitude of the oil price response, since we assume that high-skill workers continue to commute to work and thus consume oil, instead of switching to working from home. Interestingly, while price-dividend ratios of the unskilled plunge dramatically on impact and recover very slowly, the price-dividend ratio of high-skill sector experiences a persistent albeit smaller *increase*. This implication is broadly consistent with the empirically observed behavior of stock prices over the course of 2020, whereby the stock prices of "Tech" companies had reached record valuations despite the overall economy experiencing a deep recession, while the broad market and especially the "value" firms, many representing brick-and-mortar businesses heavily reliant on less-skilled labor and highly susceptible to lockdowns had lagged behind.

5 Conclusion

We build a macroeconomic model with oil entering exclusively through the commuting channel. In our model negative oil shocks have a detrimental effect for both high- and low-skilled workers. However, the relative effects on the two sectors differ. Due to the lower sensitivity of workers to commuting costs, the high-skill sector is hit less than the low-skill sector and the corresponding real wage skill premium increases. In the short term, there is little immediate impact to relative productivity. However, in the long term due to the relatively

[8] The benchmark WTI futures price even briefly became negative in April 2020, as discussed in Gilje, Ready, Roussanov and Taillard (2020).

Figure 6: COVID Lockdowns experiment within model: IRFs to negative low-skill TFP shock (deviation from the steady state) .



Note: IRFs are for negative one standard deviation of low-skill TFP shock. The variables reported are modeled in log-levels. The numbers correspond to 100*log-deviations.

milder reduction in innovation in the high-skill sector, augmented TFP in the high- skill sector eventually does relatively better than the augmented TFP in the low-skill sector. Also, model simulations and the VAR estimates show that the model generates a small response in capital to an oil price shock, as observed in the data.

As the model delivers qualitatively reasonable empirical predictions, it suggests that the commuting friction that we identify may be an important channel that contributes to oil price shock propagation in the real economy. It also provides a novel venue for understanding skill-biased technological change, since it shows that periods of high oil prices tend to increase the wage skill premium and the demand for skilled workers in the medium run.

References

Acemoglu, Daron, "Directed Technical Change," *Review of Economic Studies*, 2002, *69* (4), 781–809.

Barsky, Robert B and Lutz Kilian, "Oil and the Macroeconomy since the 1970s," *Journal of Economic Perspectives*, 2004, *18* (4), 115–134.

Baumeister, Christiane and Lutz Kilian, "Forty Years of Oil Price Fluctuations: Why the Price of Oil May Still Surprise Us," *Journal of Economic Perspectives*, February 2016, *30* (1), 139–60.

Belo, Frederico, Jun Li, Xiaoji Lin, and Xiaofei Zhao, "Labor-force heterogeneity and asset prices: The importance of skilled labor," *The Review of Financial Studies*, 2017, *30* (10), 3669–3709.

Bodenstein, Martin and Luca Guerrieri, "Oil efficiency, demand, and prices: a tale of ups and downs," International Finance Discussion Papers 1031, Board of Governors of the Federal Reserve System (U.S.) 2011.

_ , _ , and Lutz Kilian, "Monetary policy responses to oil price fluctuations," *IMF Economic Review*, 2012, *60* (4), 470–504.

Buera, Francisco J., Joseph P. Kaboski, and Richard Rogerson, "Skill Biased Structural Change," Working Paper 21165, National Bureau of Economic Research May 2015.

Comin, Diego and Mark Gertler, "Medium-Term Business Cycles," *American Economic Review*, June 2006, *96* (3), 523–551.

Fernald, John, "Productivity and Potential Output Before, During, and After the Great Recession," Working Paper 20248, National Bureau of Economic Research June 2014.

Fukunaga, Ichiro, Naohisa Hirakata, and Nao Sudo, "The Effects of Oil Price Changes on the Industry-Level Production and Prices in the U.S. and Japan," Working Paper 15791, National Bureau of Economic Research March 2010.

Gilje, Erik, Robert Ready, and Nikolai Roussanov, "Fracking, drilling, and asset pricing: Estimating the economic benefits of the shale revolution," Technical Report, National Bureau of Economic Research 2016.

_ , _ , _ , and Jerome Taillard, "The Day that WTI Died: Asset Prices and Firm Production Decisions," Technical Report, The Wharton School 2020.

Hamilton, James D., "Oil and the Macroeconomy since World War II," *Journal of Political Economy*, 1983, *91* (2), 228–248.

— , "Causes and Consequences of the Oil Shock of 2007-08," Working Paper 15002, National Bureau of Economic Research May 2009.

— , "Oil Prices, Exhaustible Resources, and Economic Growth," Working Paper 17759, National Bureau of Economic Research January 2012.

Jermann, Urban J., "Asset pricing in production economies," *Journal of Monetary Economics*, April 1998, *41* (2), 257–275.

Kaene, Michael and Eswar Prasad, "The Employment and Wage Effects of Oil Price Changes: A Sectoral Analysis," *The Review of Economics and Statistics*, Aug 1996, *78* (3), 389–400.

Kehrig, Matthias and Nicolas L. Ziebarth, "The Effects of the Real Oil Price on Regional Wage Dispersion," *American Economic Journal: Macroeconomics*, 2017.

Kilian, Lutz, "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review*, June 2009, *99* (3), 1053–69.

Kilic, Mete, "Asset Pricing Implications of Hiring Demographics," 2017.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, "Technological innovation, resource allocation, and growth," *The Quarterly Journal of Economics*, 2017, *132* (2), 665–712.

Kopytov, Alexandr, Nikolai Roussanov, and Mathieu Taschereau-Dumouchel, "Short-run pain, long-run gain? Recessions and technological transformation," *Journal of Monetary Economics*, 2018, *97*, 29 – 44.

Kung, Howard and Lucas Schmid, "Innovation, Growth, and Asset Prices," *Journal of Finance*, 06 2015, *70* (3), 1001–1037.

Mills, Edwin S, "An aggregative model of resource allocation in a metropolitan area," *The American Economic Review*, 1967, *57* (2), 197–210.

Muth, Richard F, "Cities and housing; the spatial pattern of urban residential land use.," 1969.

Olson, Mancur, "The Productivity Slowdown, the Oil Shocks, and the Real Cycle," *Journal of Economic Perspectives*, December 1988, *2* (4), 43–69.

Ready, Robert C, "Oil consumption, economic growth, and oil futures: The impact of long-run oil supply uncertainty on asset prices," *Journal of Monetary Economics*, 2018, *94*, 1–26.

Redding, Stephen J. and Matthew A. Turner, "Transportation Costs and the Spatial Organization of Economic Activity," Working Paper 20235, National Bureau of Economic Research June 2014.

Romer, Paul, "Endogenous Technological Change," *Journal of Political Economy*, 1990, *98* (5), S71–102.

Tuzel, Selale and Miao Ben Zhang, "Local Risk, Local Factors, and Asset Prices," *The Journal of Finance*, 2017, *72* (1), 325–370.

Zhang, Miao Ben, "Labor-Technology Substitution: Implications for Asset Pricing," *The Journal of Finance*, 2019, *74* (4), 1793–1839.

A Calibration

Table 4: Parameters calibrated in quarterly model

Parameter	Description	**model**
Household		
β	discount factor (quarterly)	0.996
ψ	IES	1.85
γ	Risk aversion	10
ϕ	Leisure preference	0.1
$\kappa^H = \kappa^U$	Power of Upsilon function	6
$\overline{L}^H = \overline{L}^U$	Labor resources	0.5
Production		
α^H	Capital share in high-skill	0.4
α^U	Capital share in low-skill	0.2
$\widetilde{a}$	Relative steady state of a^H to a^U	2
$\widetilde{N}$	Relative steady state of N^H to N^U	1
μ	High-skill sector weight in final output function	1
ι	Final good production elasticity parameter	0.9
δ	Depreciation of capital (quarterly)	0.02
ζ	Investment adjustment cost parameter	0.7
Endogenous growth part		
ξ^H	Patent share	0.55
ξ^U	Patent share	0.45
ν^H	Inverse markup	0.67
ν^U	Inverse markup	0.51
χ^H	Scale parameter in high-skill	0.60
χ^U	Scale parameter in low-skill	1.15
$\tau^H = \tau^U$	Patent obsolescence rate (quarterly)	0.0375
$\eta^H = \eta^U$	Elasticity of new patents with respect to R&D	0.83
Others		
ρ^A	Autocorrelation of exogenous shocks to TFP(quarterly)	0.988
ρ^T	Autocorrelation of oil supply(quarterly)	0.97
Endo Growth	Endogenous growth rate (annual)	1.83%

Note: Most of the parameters as in Kung and Schmid (2015). Leisure preference ϕ and power of Upsilon function κ calibrated to match oil-related moments in data. Sectoral capital shares α^U and α^H calibrated to match total capital share in the economy. R&D productivity scale parameters χ^U and χ^H calibrated to match growth rates in both sectors to the imposed endogenous growth rate of the economy and relative size of R&D stock equal to $\widetilde{N}$. The steady state level of total supply of oil in the economy t_{ss} is calibrated such that: the deterministic steady state level of low-skill labor $l^U_{ss} = 0.2$ keeping $a^U_{ss} = 1$ and $a^H_{ss} = \widetilde{a}$. Additional parameters of capital adjustment cost function calibrated as in Jermann (1998)

B Moments

Table 5: Macro moments - means

Moments	**model**	**data**
Oil/Output	7%	2%
Consumption/Output	45%	70%
Investment/Output	49%	28%
-Physical capital Investment/Output	20%	25%
-Intangible capital Investment/Output	29%	3.5%
Oil/Household expenditures	13%	5%-15%
Wage Skill Premium	65%	37%-65%
Sectoral comparison (high-to-low)		
Production	3.4	
Physical capital	5.5	
R&D stock	1.7	
R&D investments	3.7	
Endogenous labor productivity	1.2	
Labor	1.1	
Cost of commuting	1.9	
Marginal cost of commuting	1.7	

Table 6: Macro moments - volatilities

	model	**data**
Std Dev of Annual LogGrowth Rates		
Output	2.4%	2.3%
Investments	3.0%	6.1%
Consumption	1.8%	1.4%
Output high	2.3%	
Output low	3.3%	
Wage high	1.9%	
Wage low	2.0%	
Oil price	16.5%	10%-15%

Note: Output defined as $Output_t = C_t + I_t^H + I_t^U + S_t^U + S_t^H + P_t^O t_t$ thus it is not equal to the final goods production Y_t. Data counterparts computed by author: Total household expenditure is consumption of non-durables and services from NIPA. We also consider this measure excluding services (this generates the range of values for the ratio of oil consumption to household consumption). I is private+public investments, S is R&D investments. Oil/Output ratio - as in Ready (2018); Oil/Household expenditures as in Redding and Turner (2014). Wage skill premium as in Buera et al. (2015). Standard deviations for data as in Kung and Schmid (2015). Standard deviation of oil prices computed by author.

Table 7: Asset Pricing model moments

		model
Annual Returns		
R^f	*mean*	1.6%
	std	0.5%
$R^D - R^f$	*mean*	2.0%
	std	3.4%
$R^{R\&D} - R^f$	*mean*	0.9%
	std	0.8%
$R^{D+R\&D} - Rf$	*mean*	1.3%
	std	2.2%
$R^{D+R\&D+Oil} - Rf$	*mean*	2.0%
	std	3.2%
$R^H - R^U$	*mean*	-0.5%
	std	3.1%
$R^{Hgood} - R^{Ugood}$	*mean*	-3.3%
	std	5.0%
Quarterly correlations with log-growth of oil price		
$R^H - R^f$		-0.78
$R^U - R^f$		-0.78
$R^H - R^U$		0.37
$R^{Hgood} - R^f$		-0.79
$R^{Ugood} - R^f$		-0.80
$R^{Hgood} - R^{Ugood}$		0.43
Betas to (positive) one standard deviation of oil supply shock		
$R^H - R^f$	p.p.	0.9
$R^U - R^f$	p.p.	1.5
$R^H - R^U$	p.p.	-0.5
$R^{Hgood} - R^f$	p.p.	1.4
$R^{Ugood} - R^f$	p.p.	2.7
$R^{Hgood} - R^{Ugood}$	p.p.	-1.0

Note: R^D corresponds to the final-goods producing sector only. $R^{R\&D}$ corresonds to the intangible sector only. R^{Hgood} and R^{Ugood} corresponds to the high-skill part and low-skill part of the final-goods producing sector, where the one period dividends of the sector $j \in \{H, U\}$ are computed: $D_t^j = \frac{dY_t}{dY_t^j} Y_t^j - I_t^j - W_t^j l_t^j - \int_0^{N_t^j} P_{i,t}^j x_{i,t}^j di$. R^H and R^U includes also the profits of R&D secotrs. Betas computed by regressing $R = a + \beta_1 \epsilon_t^H + \beta_2 \epsilon_t^U + \beta_3 \epsilon_t^t$, table reports estimates of β_3.

C Equilibrium conditions

Equilibrium consists of:

1. exogenous stochastic sequences for labour productivity $\{a_t^H\}_{t=0}^{\infty}$, $\{a_t^U\}_{t=0}^{\infty}$ and oil supply $\{_t\}_{t=0}^{\infty}$
2. vector of prices $\{W_t^H, W_t^U, P_t^O, Q_t^H, Q_t^U\}_{t=0}^{\infty}$
3. low of motion $\{K_{t+1}^H, K_{t+1}^U, N_{t+1}^H, N_{t+1}^U\}_{t=0}^{\infty}$ with initial conditions $\{K_0, N_0^H, N_0^U\}$
4. sequence of allocations and other endogenous variables

$$\{U_t, C_t, l_t^H, l_t^U, m_t, I_t^H, I_t^U, Y_t, Y_t^H, Y_t^U, x_t^H, x_t^U, v_t^H, v_t^U, S_t^H, S_t^U, \vartheta_t^H, \vartheta_t^U, Z_t^H, Z_t^U\}_{t=0}^{\infty}$$

such that they satisfy the system of equations:

Household:

$$U_t = \left[(1-\beta)\Big(C_t^{1-\phi}[Trend_t(leisure_t)]^{\phi}\Big)^{1-1/\psi} + \beta\Big(E_t U_{t+1}^{1-\gamma}\Big)^{\frac{1-1/\psi}{1-\gamma}}\right]^{\frac{1}{1-1/\psi}}$$

$$W_t^H - P_t^O \Upsilon_t'^H = -\frac{\phi}{(1-\phi)}\frac{C_t}{(leisure_t)}$$

$$W_t^L - P_t^O \Upsilon_t'^L = -\frac{\phi}{(1-\phi)}\frac{C_t}{(leisure_t)}$$

$$m_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-1/\psi-\phi(1-1/\psi)}\left(\frac{Trend_{t+1}(leisure_{t+1})}{Trend_t(leisure_t)}\right)^{\phi(1-1/\psi)}\left(\frac{U_{t+1}}{E_t[U_{t+1}^{1-\gamma}]^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}$$

Final good firm:

$$K_{t+1}^H = (1-\delta)K_t^H + \Phi_t\big(I_t^H/K_t^H\big)K_t^H$$

$$K_{t+1}^U = (1-\delta)K_t^U + \Phi_t\big(I_t^U/K_t^U\big)K_t^U$$

$$K_{t+1}^H: \qquad Q_t^H = E_t\left[m_{t+1}\left(Q_{t+1}^H(1-\delta) - \frac{I_{t+1}^H}{K_{t+1}^H} + Q_{t+1}^H\Phi_{t+1}^H + MPK_{t+1}^H\right)\right]$$

$$K_{t+1}^U: \qquad Q_t^U = E_t\left[m_{t+1}\left(Q_{t+1}^U(1-\delta) - \frac{I_{t+1}^U}{K_{t+1}^U} + Q_{t+1}^U\Phi_{t+1}^U + MPK_{t+1}^U\right)\right]$$

$$Y_t = \left(\big(Y_t^U\big)^{\iota} + \mu\big(Y_t^H\big)^{\iota}\right)^{\frac{1}{\iota}}$$

$$Y_t^H = \big(K_t^H\big)^{\alpha^H}(Z_t^H l_t^H)^{1-\alpha^H}$$

$$Y_t^U = \left(K_t^U\right)^{\alpha^U} (Z_t^U l_t^U)^{1-\alpha^U}$$

$$Z_t^H = \left(\frac{\partial Y_t}{\partial Y_t^H}\xi^H\nu^H\right)^{\frac{\xi^H}{(1-\xi^H)(1-\alpha^H)}} a_{H,t}N_t^H$$

$$Z_t^U = \left(\frac{\partial Y_t}{\partial Y_t^U}\xi^U\nu^U\right)^{\frac{\xi^U}{(1-\xi^U)(1-\alpha^U)}} a_{U,t}N_t^U$$

$$Q_t^H = \frac{1}{\Phi_t'^H}$$

$$Q_t^U = \frac{1}{\Phi_t'^U}$$

$$MPL_t^H = W_t^H$$

$$MPL_t^U = W_t^U$$

Intermediate sector equations, each equation is for H and U sector $j \in \{H, U\}$

$$x_t^j = \left(\frac{\partial Y_t}{\partial Y_t^j}\xi^j\nu^j\left[(K_t^j)^{\alpha^j}(a_t^j l_t^j)^{1-\alpha^j}\right]^{1-\xi^j}(N_t^j)^{\frac{\xi^j}{\nu^j}-1}\right)^{\frac{1}{1-\xi^j}}$$

$$v_t^j = \left(\frac{1}{\nu^j} - 1\right)x_t^j + (1-\tau^j)E_t[m_{t+1}v_{t+1}^j]$$

$$N_{t+1}^j = \vartheta_t^j S_t^j + (1-\tau^j)N_t^j$$

$$\vartheta_t^j = \frac{\chi N_t^j}{(S^j)_t^{1-\eta^j}(N_t^j)^{\eta^j}}$$

$$S_t^j = E_t[m_{t+1}v_{t+1}^j](N_{t+1}^j - (1-\tau^j)N_t^j)$$

Market clearing

$$Y_t = C_t + I_t^H + I_t^U + N_t^H x_t^H + S_t^H + N_t^U x_t^U + S_t^U$$

$$t_t = \Upsilon^H(l_t^H) + \Upsilon^U(l_t^U)$$

Technology

$$log a_t^U = \rho^A log(a_{t-1}^U) + \sigma^A\epsilon_t^U$$

$$log a_t^H = log(\widetilde{a})(1-\rho^A) + \rho^A log(a_{t-1}^H) + \sigma^A\epsilon_t^H$$

$$log t_t = log(t_{ss})(1-\rho^T) + \rho^T log(t_{t-1}) + \sigma^T\epsilon_t^t$$

together with functions definitions for $\Phi(.)$ and $\Upsilon(.)$ and their derivatives $\Phi'(.)$ and $\Upsilon'(.)$ and $leisure_t$.

Note: since the economy is on the balanced growth path, thus the model in this form is non-stationary. To solve it using dynare we divide the sector-specific variables on the growth path by its sector specific N_t^j and the non-sector specific variables (Y,K,I,etc...) by N_t^H. The non-stationary (growth) variables are denoted with capital letter whereas stationary variables are denoted with small letters.

C.1 Useful relations

Because of the free movement of capital, we have $MPK_t^H = MPK_t^U$ in equilibrium, thus we have

$$\frac{\partial Y_t}{\partial Y_t^H}\frac{\partial Y_t^H}{\partial K_t^H} = \frac{\partial Y_t}{\partial Y_t^U}\frac{\partial Y_t^U}{\partial K_t^U}$$

$$(Y_t^\iota)^{\frac{1}{\iota}-1}\mu(Y_t^H)^{\iota-1}\alpha^H(1-\xi^H)\frac{Y_t^H}{K_t^H} = (Y_t^\iota)^{\frac{1}{\iota}-1}(Y_t^U)^{\iota-1}\alpha^U(1-\xi^U)\frac{Y_t^U}{K_t^U}$$

$$\left(\frac{Y_t^H}{Y_t^U}\right)^\iota = \frac{K_t^H}{K_t^U}\frac{\alpha^U(1-\xi^U)}{\mu\alpha^H(1-\xi^H)}$$

$$\frac{Y_t}{Y_t^U} = \left(1+\frac{K_t^H}{K_t^U}\frac{\alpha^U(1-\xi^U)}{\alpha^H(1-\xi^H)}\right)^{\frac{1}{\iota}}$$

$$\frac{Y_t}{Y_t^H} = \left[\mu\left(1+\frac{K_t^H}{K_t^U}\frac{\alpha^U(1-\xi^U)}{\alpha^H(1-\xi^H)}\right)\right]^{\frac{1}{\iota}}$$

$$\frac{\partial Y_t}{\partial Y_t^j} = [\mu(Y^H)_t^\iota + (Y^U)_t^\iota]^{\frac{1}{\iota}-1}\mu^{\mathbb{1}\{j=H\}}(Y^j)_t^{\iota-1} = [Y_t^\iota]^{\frac{1}{\iota}-1}\mu^{\mathbb{1}\{j=H\}}(Y^j)_t^{\iota-1} = \mu^{\mathbb{1}\{j=H\}}\left(\frac{Y_t^j}{Y_t}\right)^{\iota-1}$$

$$MPK^j = \frac{\partial Y_t}{\partial Y_t^j}\frac{\partial Y_t^j}{\partial K_t^j} = \frac{\partial Y_t}{\partial Y_t^j}\alpha^j(1-\xi^j)\frac{Y_t^j}{K_t^j}$$

$$MPL^j = \frac{\partial Y_t}{\partial Y_t^j}\frac{\partial Y_t^j}{\partial l_t^j} = \frac{\partial Y_t}{\partial Y_t^j}(1-\alpha^j)(1-\xi^j)\frac{Y_t^j}{l_t^j}$$

$$P_t^O\left(\Upsilon_t'^H(l_t^H) - \Upsilon_t'^U(l_t^U)\right) = W_t^H - W_t^U = MPL_t^H - MPL_t^U$$

Extra definitions:

$$Trend_t = \overline{EndoGrowth} * Trend_{t-1}$$

$$Ngap_t^j = \frac{N_t^j}{Trend_t} = \frac{N_t^j}{N_{t-1}^j}\frac{Trend_{t-1}}{Trend_t}\frac{N_{t-1}^j}{Trend_{t-1}} = \frac{N_t^j}{N_{t-1}^j} * \overline{EndoGrowth}^{-1} * Ngap_{t-1}^j$$

C.2 Explanation of Transformed IRFs

Level variables need to be transformed into stationary due to growth. Sector-specific levels are divided by sector specific N_t^j, global levels are divided by N_t^H. This is why in the IRF function of the stationarized version, not only variable itself, but also its denominator is affected by the shock. Thus to unwind the effect shock has on the denominator, we compute the transformed IRFs in the following way:

Non-transformed IRF:

$$IRF^{t+k} = \frac{Y_{t+k}}{N_{t+k}}$$

Transformed IRF:

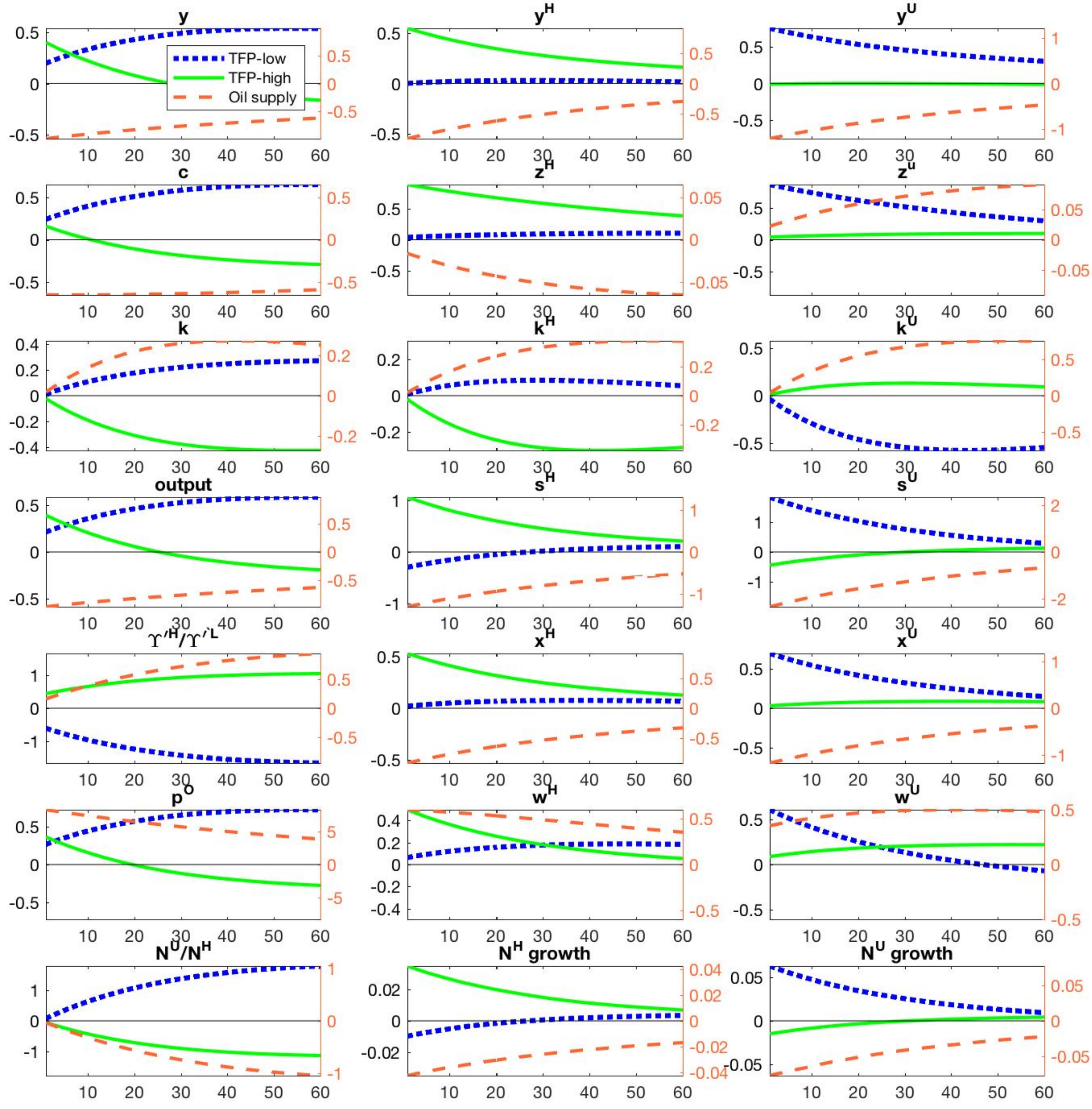
$$\widetilde{IRF}^{t+0} = \frac{Y_{t+0}}{Trend_{t+0}} = IRF^{t+0}\frac{N_{t+0}}{Trend_{t+0}} = IRF^{t+0}$$

$$\widetilde{IRF}^{t+1} = \frac{Y_{t+1}}{Trend_{t+1}} = IRF^{t+1}\frac{N_{t+1}}{Trend_{t+1}}$$

$$\widetilde{IRF}^{t+2} = \frac{Y_{t+2}}{Trend_{t+2}} = IRF^{t+2}\frac{N_{t+2}}{Trend_{t+2}}$$

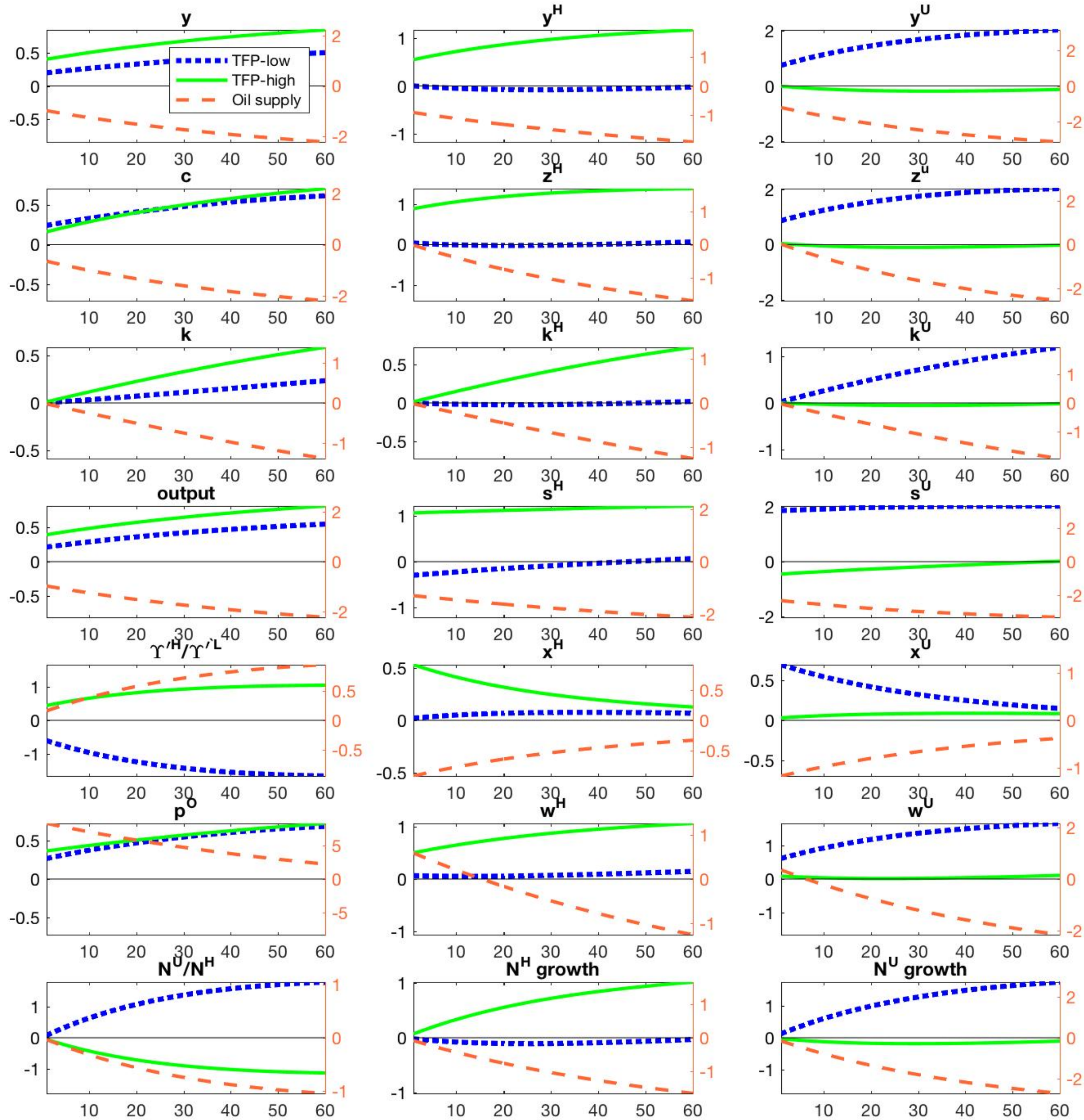
D Extra figures

Figure 7: IRF to all shocks - part 1



Note: Left axis corresponds to the impulse response to one standard deviation of (positive) TFP shocks. Right axis corresponds to the impulse response to the one standard deviation of (negative) oil supply shock, quarterly periods on x-axis. Capital variables (K, K^H, K^U) and R&D stock (N^H, N^U) variables are pre-determined in the model and as such period t on x-axis corresponds to response at t+1. $\text{Output}_t = C_t + I_t^H + I_t^U + S_t^H + S_t^U + Oil_t$.

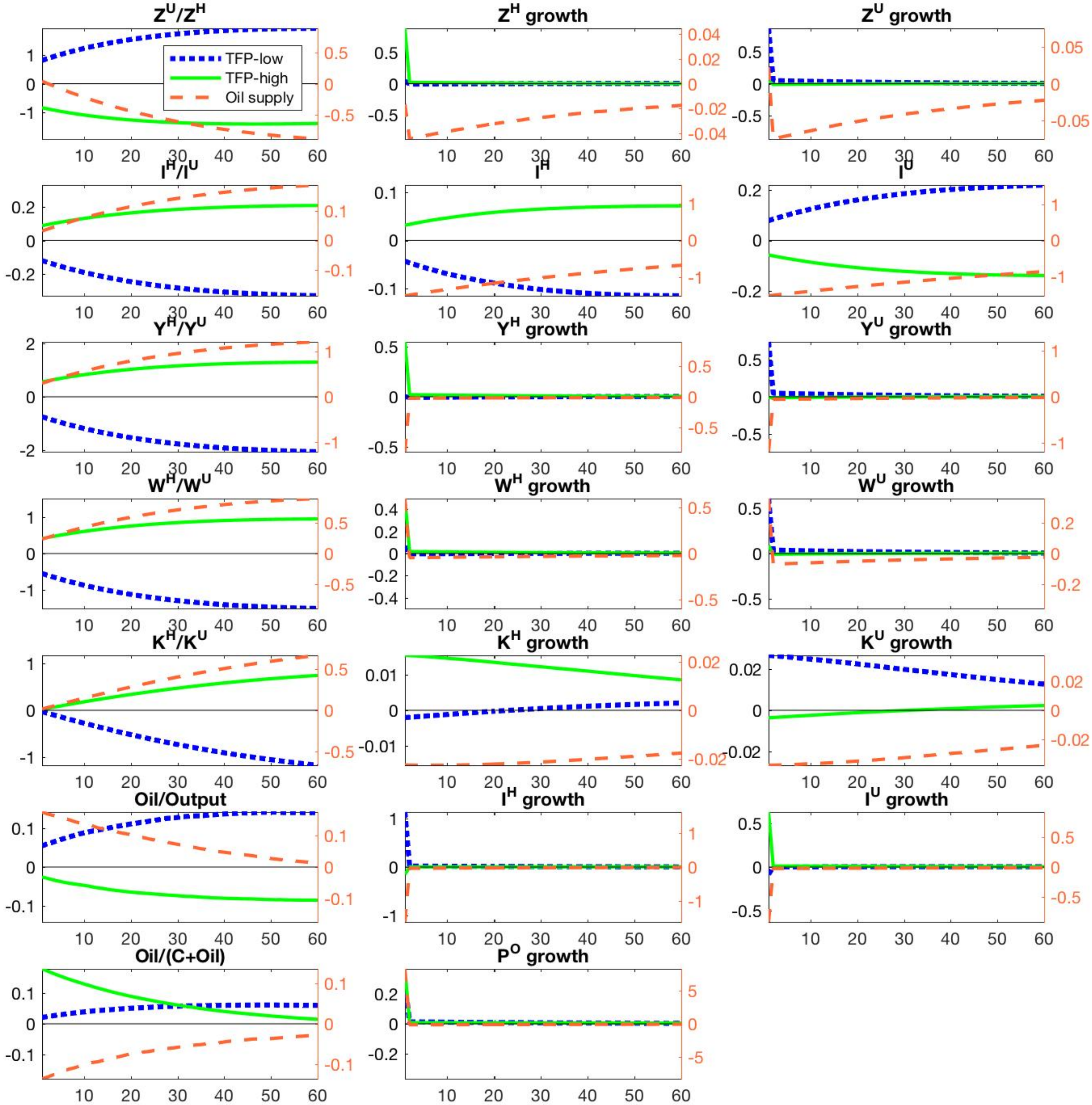
Figure 8: Transformed RF to all shocks - part 1[9]



Note: Left axis corresponds to the impulse response to one standard deviation of (positive) TFP shocks. Right axis corresponds to the impulse response to the one standard deviation of (negative) oil supply shock, quarterly periods on x-asix. Capital variables (K, K^H, K^U) and R&D stock (N^H, N^U) variables are pre-determined in the model and as such period t on x-axis corresponds to response at t+1. Output$_t = C_t + I_t^H + I_t^U + S_t^H + S_t^U + Oil_t$.

[9] Variables on the balanced growth-path are transformed to unwind the effect shock has on the denominator. For more explanation please look into the section E.2 of the appendix.

Figure 9: IRF to all shocks - part 2



Note: Left axis corresponds to the impulse response to one standard deviation of (positive) TFP shocks. Right axis corresponds to the impulse response to the one standard deviation of (negative) oil supply shock, quarterly periods on x-asix. Capital variables (K, K^H, K^U) and R&D stock (N^H, N^U) variables are pre-determined in the model and as such period t on x-axis corresponds to response at t+1.