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Abstract

We find that oil supply shocks decrease average real wages, particularly skilled wages, and increase wage dispersion across regions, particularly unskilled wage dispersion. In a model with spatial energy intensity differences and nontradables, labor demand shifts, while explaining the response of average wages to oil supply shocks, have counterfactual implications for the response of wage dispersion. Only an additional response in labor supply can explain this latter fact highlighting the importance of general equilibrium effects in a spatial context. We provide additional empirical evidence of regionally directed worker reallocation and housing prices consistent with our spatial model. Finally, we show that a calibrated version of our model can quantitatively match the estimated effects of oil supply shocks.

JEL-Codes: E240, J240, J310, J610.

Keywords: wage dispersion, labor reallocation, skill heterogeneity, oil prices.

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1 Introduction

Recently, Polgreen and Silos (2009) have documented that the real oil price is one driver of high-frequency variation in the skill premium. They argue that an energy-skill complementarity in the production function can explain the fact that, empirically, the skill premium falls after an unexpected increase in the real price of oil. Under this complementarity, labor demand for the skilled falls more than for the unskilled. However, it is not just that skilled labor demand falls more when the real oil price rises but that it falls more in regions where production relies heavily on energy (say steel production in Pittsburgh) than in those that do not (say food processing in Philadelphia). These changes in local labor demand induce changes in local labor supply, and these induced changes in labor supply have important implications for understanding not just differences in wages between skill groups but also differences across regions.

We build a model has three central features to analyze the responses to exogenous shocks to the real price of oil: regional differences in energy intensity, an energy-skill complementarity as empirically estimated by Polgreen and Silos (2009), and spatial labor reallocation. After an exogenous shock to the real oil price, labor demand falls asymmetrically across regions. The drop in labor demand is not only uneven across regions, but also across skill groups. Due to the energy-skill complementarity, the second key feature in our model, demand for skilled labor falls more than demand for unskilled labor. Due to the asymmetric response of labor demand across regions and skill groups, wage prospects, particularly those for skilled workers, initially diverge, all else being equal. If there are different wage prospects across regions, workers have an incentive to reallocate to high-wage regions. This spatial labor reallocation is the third key factor in our model. The degree of reallocation as in the paper by Roback (1982) is determined by the prices of both tradeable consumption goods and non-tradeable goods such as housing or local services, which have to be purchased in the same region in which they reside and work.

Given the different wage prospects, skilled workers in particular have an incentive to relocate and they will increasingly concentrate in regions where firms operate energy-efficient technologies and pay higher wages. The concentration of labor in high-wage regions, however, drives up local living costs such as housing rent and non-tradeable services, while the opposite is true in out-migrating regions. This means that unskilled workers that would have considered relocating to a high-wage region may actually decide to stay in a low-wage region because they profit from lower living expenses. As a consequence, changes in the relative supply of skilled labor dampen the direct effect of the asymmetric labor demand response, so that skilled wage dispersion, in the end, is more or less unchanged.

Because unskilled workers relocate very little, increases in the spread of unskilled wages remain. The unskilled are then compensated for an adverse shift in wages by a favorable shift in living costs. Our model implies that, once adjustments are made for local price indexes, real wage inequality within skill groups is drastically lowered. So as in other work on the relationship between the cost of living and wages, for example, by Moretti (2013), Eeckhout, Pinheiro and Schmidheiny (2014), and Albouy and Ehrlich (2012), wage inequality is not necessarily evidence of inefficiency or, in our case, even explicit moving costs. The important point of comparison is to a model with a fixed supply of labor of the two types across space, which is isomorphic to the original work by Polgreen and Silos (2009). We show that the predictions for first moments such as the skill premium are the same as in our model with flexible local labor supply. At the same time, the effect of shocks to the real oil price on wage dispersion are completely different between the two models. Unskilled wage dispersion does *not* change and skilled wage dispersion is affected. These differences provide a clear separation of a model that takes the supply of labor as fixed and one where endogenous worker choices determine the supply of labor.

To summarize, in our model with flexible labor supply, the adjustment to an exogenous shock to the real oil price among skilled workers is mitigated through reallocation, while changes in local prices are central for unskilled workers. Crucially, only a combination of labor demand and labor supply changes can explain both the response of wage levels and wage dispersion. Our model has two main implications that can differentiate between a fixed versus flexible local labor supply model. First, when an exogenous shock drives up the real oil price, unskilled wage dispersion rises and skilled wage dispersion increases only moderately compared to unskilled wage dispersion; the converse is true about the dispersion of skilled and unskilled employment.

We test empirically a variety of the model's implications using confidential establishment-level data from the Current Population Survey. First, employing the method suggested by Kilian (2009) to disentangle endogenous and exogenous movements in the real oil price, we find that cross-sectional dispersion of unskilled wages increases significantly in the wake of a shock to the supply of oil.[1] For example, a one standard deviation negative shock to oil supply that increases the real price of oil leads to a rise in the cross-county standard deviation of wages by around 3.6% on impact and 3.0% with a one year lag. For skilled workers, there is no effect at all. Third, using the Current Population Survey (CPS) we find evidence for differential migration rates between skilled and unskilled in response to shocks to the real price of oil. In particular, we find that skilled migration rates rise by a quarter following such a shock and that migration is directed away from the energy intensive areas. Finally, we find that exogenous shocks to the real price of oil decrease housing prices in energy inefficient areas while, in some specifications, increasing them in energy efficient areas.

A final exercise involves calibrating the model to match the estimated effects outlined above. While being very parsimonious, we show that our model's quantitative effects to a shock to the price of oil are quite close to the estimated ones. While the model explains the differential change in wage dispersion across the skill groups well, one shortcoming of the model is in overshooting the percentage change in wage dispersion of the two groups. This seems to be due to the fact that the model underestimates the level of wage dispersion to begin with, unsurprising since the only source of dispersion comes from energy intensity dispersion across regions.

Our paper is part of a revival in the broader macro literature on the role of reallocation for aggregate fluctuations. In those models, because labor reallocation is hampered by frictions, firm-specific or sector-specific shocks lead to wage dispersion in equilibrium and fluctuations in output as workers can only be slowly reallocated. The reallocation literature goes back to Lilien (1982); Davis and Haltiwanger (1999) and has been reinvigorated in Garin et al. (2011): sectoral shocks lead to wage dispersion and unemployment. This result arises because sectoral labor reallocation is

[1]In an appendix using the Annual Survey of Manufactures, we document the oil-skill complementarity at the establishment-level.

obstructed by frictions. For example, Shimer (2007) studies search frictions that delay reallocation between sectors while Wasmer and Zenou (2006) focus on frictions in the spatial aspect of reallocation. Our model focuses on one particular shock that induces a need for reallocation across industries and regions: the real oil price. Hamilton (1988) has studied the impact of exogenous real oil price shocks on the allocation of specialized factors.

Macroeconomists have traditionally focused on the impact of shocks to the real price of oil on the standard macro aggregates such as output, investment and inflation. See Hamilton (1983, 2003), Kim and Loungani (1992), Kilian (2008) on output, Kilian and Park (2011) on the stock market, Kilian and Vigfusson (2011, 2013); Baumeister and Peersman (2013) on non-linear responses over the cycle and Edelstein and Kilian (2009) on consumer expenditures; Baumeister and Kilian (2016) give a recent summary of the literature. Others such as Loungani (1986) and Rupert et al. (2009) have argued that the reallocation process is hampered by commuting costs, some of which consists of a higher real oil price. We abstract from these effects on commuting costs and focus on only the differential labor demand effects and the induced labor supply response. Finally, there has been some work by Keane and Prasad (1996), Davis and Haltiwanger (2001), Lee and Ni (2002) and Herrera and Karaki (forthcoming) that has studied the sectoral effects of shocks to the real price of oil. We reinterpret these sectoral differences as geographic differences from the concentration of particular industries in particular locales.

2 The model

We formulate a spatial model where differences in energy intensity, labor reallocation and local housing prices deliver rising unskilled wage dispersion, while skilled wage dispersion rises only moderately or remains stagnant. For tractability, we limit our analysis to two regions although the model could be extended to N regions without affecting the main results.

2.1 Firms and labor demand

We begin by studying the case of fixed labor supply and then allow workers to reallocate in response to real oil price shocks. There are two regions, denoted by i and j, each with a continuum of competitive firms. We adopt a nested CES production technology which is a special case of Polgreen and Silos (2009) who in turn follow Krusell et al. (2000). This leads to a fall in the skill premium in response to a real oil price shock.[2] We want to preserve this result while keeping the analysis of relative wages and relative employment simple and tractable, which is why we choose a Cobb Douglas-Leontief formulation. In particular, firms produce output and sell it into a world market at a (normalized) fixed price of 1 using the following technology:

$$y_i = u_i^{\alpha} \left[\min \{ s_i, \gamma_i e_i \} \right]^{1-\alpha} \tag{1}$$

where y_i is output, u_i and s_i are unskilled and skilled labor respectively, while e_i is energy consumed. α and γ_i are technology parameters that govern factor shares. γ_i is of particular interest as it determines the energy intensity of firms in region i. The higher γ_i, the more fuel-efficient are firms. Without loss of generality, we assume that $\gamma_i > \gamma_j$. We are aware that the strict complementarity between skilled labor and energy is an extreme assumption, but none of our qualitative results about wage dispersion within and between skill groups are affected by it.[3]

We abstract from technological differences *within* a region and assume that all firms operate the same technology. We could relax that assumption and assume another spatial dimension (within-region heterogeneity) involving commuting between different neighborhoods. Guerrieri et al. (2009) have shown that this can generate within-region dispersion of housing prices and – in our context – also within-region wage dispersion. Because we are interested in explaining the general energy-wage dispersion relationship, we focus on *between-region* differences in energy intensity. This

[2] To be precise, Polgreen and Silos (2009) confirm a well-known capital-skill complementarity and a capital-unskilled substitutability. They go further to show empirically that capital and energy are complements too. Combining these two results implies a skill-energy complementarity and an unskilled-energy substitutability. Without changing the main result about wages of skill groups we omit capital here to simplify the analysis.

[3] In an appendix, we provide empirical evidence from the Annual Survey of Manufactures for this complementarity.

focus is supported by the results in Davis et al. (1997) who found vast geographical differences in responses to real oil price shocks. The Census Bureau's Manufacturing Energy Consumption Survey (MECS) shows that energy intensity between Census regions varies greatly (see Table 1). Even within fairly homogeneous industries such as steel, paper or chemicals there is significant variation in energy intensity across the U.S. with the standard deviation being about two thirds of the mean.[4] We present further evidence from the Census' Annual Survey of Manufactures on energy intensity differences between counties and MSA's in the bottom panel of Table 2.

Both skilled labor and energy are chosen by the firm in the same period and free of any adjustment constraints. Then the strict complementarity immediately dictates the optimal relationship between the use of energy and skilled labor:

$$e_i = \frac{s_i}{\gamma_i}$$

For energy-efficient firms the skill-energy ratio will be higher than in energy-inefficient (or energy intensive) firms. The real oil price, q, is determined outside of the model and taken as given by firms. To emphasize, the real oil price is the price denoted in terms of output. Wages for unskilled, w_i^u, and skilled labor, w_i^s, are also taken as given by firms but will be determined endogenously.

$$w_i^u = \alpha \left(\frac{s_i}{u_i} \right)^{1-\alpha} \tag{2}$$

$$w_i^s = (1-\alpha) \left(\frac{s_i}{u_i} \right)^{-\alpha} - \frac{q}{\gamma_i} \tag{3}$$

Equation (3) shows that labor demand for skilled workers is higher the less energy-dependent its production (the higher γ_i). Unskilled labor demand, in contrast, is not influenced by the real oil price directly, which is a consequence of our Cobb-Douglas assumption between unskilled labor and the other production factors. Note that the skill premium need not be larger than 1. We identify skilled workers as ones whose labor is complementary with energy rather than assuming that they are relatively

[4] We additionally studied the dispersion of oil intensity only which results in similar regional dispersion.

Table 1: Spatial heterogeneity in energy intensity
(thousand BTU per $ value added)

NAICS	Industry	All U.S. Mean	Regional Dispersion Std. Dev.	CV
311	Food	4.000	1.426	0.356
312	Beverage and Tobacco	1.425	0.538	0.377
313	Textile Mills	5.000	2.568	0.514
314	Textile Product Mills	2.400	2.168	0.903
315	Apparel	0.950	0.495	0.521
316	Leather and Allied	1.000	0.548	0.548
321	Wood	17.925	10.647	0.594
322	Paper	24.425	10.172	0.416
323	Printing and Related Support	2.033	0.603	0.296
324	Petroleum and Coal	43.050	21.234	0.493
325	Chemicals	5.475	3.497	0.639
326	Plastics and Rubber	2.975	0.922	0.310
327	Nonmetallic Minerals	15.375	1.761	0.115
331	Primary Metals	16.100	6.773	0.421
332	Fabricated Metals	1.700	0.716	0.421
333	Machinery	0.825	0.330	0.400
334	Computer and Electronics	0.725	0.096	0.132
335	Electrical Equipment	1.500	0.668	0.446
336	Transportation Equipment	0.950	0.342	0.360
337	Furniture	1.025	0.544	0.531
339	Miscellaneous	0.650	0.265	0.407

Note: Table displays energy intensity differences across the four main Census regions for major manufacturing industries.
Source: 2010 Manufacturing Energy Consumption Survey, Table 6.1, and authors' calculations.

scarcer, which would provide a basis for a skill premium.

We now analyze how the skill premium and wage dispersion respond to a real oil price shock both without and with migration. The standard definition of the skill premium for region i and the wage dispersion for skill group k are

$$SP_i \equiv \frac{w_i^s}{w_i^u} = \frac{1-\alpha}{\alpha}\left(\frac{s_i}{u_i}\right)^{-1} - \frac{q}{\alpha\gamma_i}\left(\frac{s_i}{u_i}\right)^{\alpha-1}$$
$$V(w^k) = \sum_i k_i(w_i^k - \overline{w}^k)^2 = k_i(1-k_i)(w_i^k - w_j^k)^2$$

where we've used properties of a bivariate variable. Inspection of the expression for the skill premium and wage dispersion leads us to a preliminary result when labor remains fixed. We collect all proofs in the appendix.

Proposition 2.1 *If energy is more complementary to skilled labor than to unskilled labor and if the allocation of labor is fixed, then all else equal an unexpected increase in the real oil price*

- *reduces the skill premium (Polgreen and Silos (2009)),*
- *does* not *affect unskilled wage dispersion.*

This first part of result holds as long as skilled labor and energy are more complementary than unskilled labor and energy. As mentioned above, the demand curve for skilled labor shifts down in all regions, while the demand curve for unskilled labor does not shift at all. With a fixed labor supply, skilled wages fall everywhere and unskilled wages stay constant thus depressing the skill premium. Proposition 2.1 shows that without changes in the *allocation* of labor across regions, any observed changes in the dispersion of unskilled wages cannot be explained by differences in energy intensity and subsequent changes in labor demand. Also, depending on the assumed exogenous labor supply, skilled wage dispersion may increase or decrease. This highlights the need to explicitly model labor supply and how it endogenously responds to the real oil price in light of differences in energy intensity.

2.2 Households

There is a measure 1 of both unskilled and skilled workers in the economy. Each worker first decides in which region to reside and work. We make the common assumption that workers inelastically supply their labor in whatever region they reside. A worker from skill group k residing in region i is paid real wage w_i^k which he uses to purchase consumption goods c_i^k and "housing" h_i^k. We use the term housing for simplicity, but really we have in mind any non-tradeables produced locally in region i. These non-tradeables make up a large fraction of the CPI with housing alone comprising almost 43% of the basket. Consumption is our numéraire and it is traded on a world market which is big enough so changes in local demand do not affect the price. The price of one unit of housing in terms of consumption is r_i. In contrast to consumption, housing is a locally produced and supplied good and we require workers to purchase their housing in the same region where they work and reside. They maximize the following utility function

$$
\begin{aligned}
u(h^k, c^k) &= (h_i^k)^{\theta^k}(c_i^k)^{1-\theta^k} \\
\text{s.t. } c_i^k + r_i h_i^k &\leq w_i^k
\end{aligned}
$$

where θ^k is the expenditure share of housing in skill group k. The first order conditions give rise to the following demand curves for housing and consumption

$$r_i h_i^k = \theta^k w_i^k \tag{4}$$

$$c_i^k = (1 - \theta^k) w_i^k. \tag{5}$$

We want to point out that both skill groups consume the same goods though the quantity will vary with income levels (w^k) and preferences (θ^k). Thus, we can write aggregate demand for housing and consumption in region i as

$$
\begin{aligned}
H_i^D &= h_i^u u_i + h_i^s s_i \\
&= \frac{\theta^u w_i^u}{r_i} u_i + \frac{\theta^s w_i^s}{r_i} s_i && (6) \\
C_i^D &= c_i^u u_i + c_i^s s_i \\
&= (1 - \theta^u) w_i^u u_i + (1 - \theta^s) w_i^s s_i && (7)
\end{aligned}
$$

The market for housing is local and the price of housing, r_i, may differ across regions. Following the urban literature (see for example Notowidigdo (2010)) we assume that housing is supplied by landlords who are not active in labor or goods markets.[5] Since we do not explicitly model their objective, we simply assume that the resulting supply curve of housing in region i is

$$
r_i = h_i^\beta \tag{8}
$$

where we assume that $\beta > 0$.[6] Contrary to the (implicit) consumption supply curve which is flat, the housing supply curve slopes upward. This reflects the property that housing is in scarce supply at least in the short run. Housing prices respond to demand and are, hence, the key determinant of a household's purchasing power and utility. Together with wages, housing prices hence determine in which region the household will supply its labor.

Combining equations (6) and (8), the equilibrium housing price in region i is

[5]We may also assume that skilled high-income workers own houses which would make the model's predictions about wage dispersion more pronounced: skilled workers would reallocate even faster to high-wage regions since their income loss is even higher. The models prediction about wage dispersion would only weaken if we implausibly assumed that unskilled workers own houses and skilled workers do not.

[6]We could explicitly model housing being produced by the local firm alongside the intermediate good that goes into final production. All that matters is that the resulting supply curve is strictly upward sloping.

$$
\begin{aligned}
H_i^S(r_i^*) &= H_i^D(r_i^*) \\
r_i^* &= \left[\frac{\theta^u w_i^u}{r_i^*} u_i + \frac{\theta^s w_i^s}{r_i^*} s_i\right]^{\beta} \\
r_i^* &= \left[\theta^u w_i^u u_i + \theta^s w_i^s s_i\right]^{\frac{\beta}{1+\beta}} \qquad (9)
\end{aligned}
$$

Note that the equilibrium a region's housing price is increasing in the number of people living in the region $(s_i + u_i)$. For the solution of the endogenous supply of labor, it is convenient to know the ratio of economy-wide housing prices

$$
\frac{r_i}{r_j} = \left\{ \frac{\left[1 + \tilde{\theta} \frac{w_i^s s_i}{w_i^u u_i}\right]}{\left[1 + \tilde{\theta} \frac{w_j^s s_j}{w_j^u u_j}\right]} \frac{w_i^u u_i}{w_j^u u_j} \right\}^{\frac{\beta}{1+\beta}} \qquad (10)
$$

where $\tilde{\theta} \equiv \theta^s/\theta^u$.

2.3 Labor reallocation

Workers can migrate from region i to region j at no cost. Then consider a household in region j that thinks about migrating to region i (or vice versa). Using the above demand curves (Eqns. (4) and (5)), she compares her indirect utility in both regions given the respective wage offers and housing prices. The indirect utility can be written as

$$
v(c_i^k, h_i^k) = \left(\frac{\theta^k}{r_i}\right)^{\theta^k} (1 - \theta^k)^{1-\theta^k} w_i^k
$$

In equilibrium, she must be indifferent between staying and moving:

$$
v(c_i^k, h_i^k) = v(c_j^k, h_j^k) \qquad (11)
$$

This implies that housing price ratios have to be equal to functions of wage ratios for skilled and unskilled workers.

$$\frac{r_i}{r_j} = \left(\frac{w_i^u}{w_j^u}\right)^{\frac{1}{\theta^u}} \quad \text{and} \tag{12}$$

$$\frac{r_i}{r_j} = \left(\frac{w_i^s}{w_j^s}\right)^{\frac{1}{\theta^s}} \tag{13}$$

Equations (12) and (13) indicate a no-migration condition and have to hold in equilibrium. Plugging in equations (2), (3) and (21) gives two equilibrium conditions. Noting that $1 = u_i + u_j = s_i + s_j$ these two conditions determine the equilibrium allocation of skilled and unskilled labor across regions $\{s_i, u_i\}$. At this allocation, an individual unskilled or skilled worker is indifferent to migrating to the other region, household utility and firm profits are maximized. Equations (2) and (3) determine equilibrium wages, equation (9) equilibrium housing prices, and equations (6) and (7) housing and consumption quantities in all regions.

2.4 The impact of a real oil price shock with migration

The conditions governing equilibrium, equations (2), (3), (9), (12) and (13), imply that there are no wage or rent differences between regions. Hence, there is no wage and housing price dispersion. With differences in energy intensity, the real oil price matters for the allocation of labor, wages and housing prices. In particular, the allocation of labor is skewed in favor of the more energy-efficient region, which has higher wages for all skill groups and also higher housing prices. For convenience let

$$\tilde{s}_\ell = \frac{s_\ell}{u_\ell} \qquad \ell = i, j$$

Note that given $\tilde{s}_i, \tilde{s}_j$, we can express actual employment levels for each skill group:

$$u_i = \frac{1-\tilde{s}_j}{\tilde{s}_i - \tilde{s}_j}$$
$$s_i = \frac{\tilde{s}_i(1-\tilde{s}_j)}{\tilde{s}_i - \tilde{s}_j}$$

Using these expressions, we can rewrite the two no-migration conditions that define the solution for $\tilde{s}_i$ and $\tilde{s}_j$.

$$\left(\frac{\tilde{s}_i}{\tilde{s}_j}\right)^{\frac{(1-\alpha)}{\tilde{\theta}}} = \frac{\tilde{s}_i^{-\alpha}(1-\alpha) - \frac{q}{\gamma_i}}{\tilde{s}_j^{-\alpha}(1-\alpha) - \frac{q}{\gamma_j}} \tag{14}$$

$$\left(\frac{\tilde{s}_i}{\tilde{s}_j}\right)^{\frac{(1-\alpha)}{\theta_u}} = -\left[\frac{\tilde{s}_i(1-\tilde{s}_j)}{\tilde{s}_j(1-\tilde{s}_i)}\left(\frac{\tilde{s}_i^{-\alpha}(\alpha\tilde{\theta}+1-\alpha) - \frac{q}{\gamma_i}}{\tilde{s}_j^{-\alpha}(\alpha\tilde{\theta}+1-\alpha) - \frac{q}{\gamma_j}}\right)\right]^{\frac{\beta}{1+\beta}} \tag{15}$$

where $\tilde{\theta} = \theta_u/\theta_s$. Now we can show that skilled workers will concentrate in the energy-efficient region more than unskilled workers do.

Proposition 2.2 *For any positive real oil price, the equilibrium skill intensity, wages and rents are higher in the energy-efficient region: If $q > 0$ and $\gamma_i > \gamma_j$, then $\tilde{s}_i > \tilde{s}_j$, $w_i^s > w_j^s$, $w_i^u > w_j^u$ and $r_i > r_j$.*

The intuition here is quite clear. Because the skilled workers are complements to energy, it is profitable to have relatively more of them where energy is used most efficiently. Because skilled and unskilled labor are complements, it is more profitable to have many unskilled workers around where skilled workers are. Because both skilled and unskilled workers concentrate in the energy-efficient region, this high demand for housing will drive up rents while slack demand for housing in the energy-inefficient city will lead to low rents.

For the rest of the results, we study an approximate solution around a balanced allocation $s_i = s_j = u_i = u_j = 1/2$. This obtains when $q = 0$ or if both regions have the same energy intensity ($\gamma_i = \gamma_j$). We we focus on the empirically plausible case of a fairly balanced allocation since if q gets too large, then all economic activity concentrates in the most energy efficient region. This seems like an artifact of the feature that it is impossible for technological reasons to substitute away from high priced energy. Precisely, we assume

ASSUMPTION 1 $\gamma_j > \frac{q}{\alpha\tilde{\theta}+1-\alpha}$.

This will also hold for γ_i as well since by assumption $\gamma_i > \gamma_j$.

We can then calculate the linearized solution as follows

Proposition 2.3 (Linearized Solution) *An approximate solution for $\tilde{s}_i, \tilde{s}_j$ around 1 is given by*

$$\tilde{s}_i - 1 = \frac{\omega_i \omega_j^2 \tilde{\theta} q \left(\frac{1}{\gamma_j} - \frac{1}{\gamma_i}\right)}{(\omega_j^2 + \omega_i^2)(1-\alpha)} > 0 \tag{16}$$

$$\tilde{s}_j - 1 = -\frac{\tilde{\theta} q \omega_i^2 \omega_j \left(\frac{1}{\gamma_j} - \frac{1}{\gamma_i}\right)}{(\omega_j^2 + \omega_i^2)(1-\alpha)} < 0 \tag{17}$$

where

$$\omega_k = \frac{1}{\alpha\tilde{\theta} + 1 - \alpha - \frac{q}{\gamma_k}}.$$

The technical assumption ensures that $\omega_k > 0$ for all k. With this, we can calculate the economy-wide skill premium as a weighted average of the two regions' skill premium. Because the energy-efficient region (where the skill premium falls for sure) attracts more people overall, the negative effect in that region will dominate the possibly positive one in the energy-inefficient region. So we have

Proposition 2.4 *Under the linear approximation and all else equal, an unexpected increase in the real oil price increases the skill intensity and decreases the skill premium in the energy-efficient region while in the energy-inefficient region it decreases the skill intensity and has an ambiguous effect on the skill premium: $\frac{\partial \tilde{s}_j}{\partial q} < 0$, $\frac{\partial \tilde{s}_i}{\partial q} > 0$, and $\frac{\partial \tilde{s}_i}{\partial q} < 0$.*

We point out some interesting comparative statics here. First, larger differences in energy intensity $(\gamma_i - \gamma_j)$ increase the effect of real oil price shocks. The bigger the energy intensity gap, the greater the pressure to reallocate in the face of a shock to the real oil price. Skilled workers reallocate very quickly compared to unskilled workers. The energy-skill complementarity in our production technology is behind this asymmetry. The asymmetric effect of real oil price shocks on skilled to unskilled labor reallocation are accentuated by large differences in how the two skill groups value housing. If $\theta_u \gg \theta_s$, then the unskilled are even less likely to move with the skilled as they value affordable housing much more. One thing to note is that β, the elastic region of the housing supply curve, does not affect the asymmetry. Instead more inelastic supply curves slow reallocation.

Now we are in position to derive our central result.

Proposition 2.5 *Under the linear approximation, all else equal, an unexpected increase in the real oil price increases both unweighted and weighted unskilled wage dispersion:* $\frac{\partial(w_i^u - w_j^u)}{\partial q} > 0$ *and* $\frac{\partial V(w^u)}{\partial q} > 0$*, but skilled wage dispersion increases by less than unskilled wage dispersion:* $0 < \frac{\partial \log V(w^s)}{\partial q} < \frac{\partial \log V(w^u)}{\partial q}$.

The logic of our last two results is as follows. If the real oil price q rises, then the labor demand for skilled shifts inwards suppressing skilled wages in both regions. The fact that only the skilled labor demand curve decreases is due to energy and skilled labor being strict complements. The demand curve for unskilled labor does not shift because unskilled labor and energy/skilled labor have a unit elasticity of substitution. This above-described inward shift is comparatively weak in region i, which is more energy-efficient ($\gamma_i > \gamma_j$). Hence, there will be migration pressure for skilled workers to move to region i. This migration increases the ratio of skilled to unskilled labor in region i and makes unskilled labor relatively scarce in region i. Therefore, some unskilled workers now follow the skilled migrants to region i where they can earn a higher wage.

Beware that unskilled migration is much weaker than skilled migration because it just responds to an abundance of skilled workers in the energy-efficient region and is not directly affected by a real oil price shock. Although unskilled follow skilled workers, the ratio of skilled to unskilled labor, s_i/u_i, in the new equilibrium will be still higher than in the old one. Overall migration increases housing demand in region i driving up housing prices r_i, so, eventually, migration comes to a stop when housing prices are so high that further migration would not increase utility of a worker although he would get a higher wage in region i. Lower housing prices in region j due to skilled out-migration are like a positive externality for unskilled that makes them more inclined to stay despite lower wages.[7] Hence, even though there are large changes in the allocation of skilled workers, this has little impact on skilled weighted wage dispersion because the range of skilled wages is so low. Note the interesting general equilibrium effect on wage dispersion here. Even though the initial incidence of the real oil price shock falls most strongly on the skilled due to complementarities, they, in the end, see the least impact on wage dispersion because they adjust their labor supply.

3 Empirical evidence

Our empirical analysis consists of two separate parts. First, we will provide evidence that changes in skilled and unskilled wage dispersion in response to an oil supply shock that raises the real price of oil are consistent with our model. This will be done using establishment-level information from the labor demand side. Second, we will show that, in response to these oil supply shocks using worker-level information, changes in local labor supply as reflected in migration patterns are broadly in line with the model.

3.1 Data Sources

We use two sources of information: confidential data from the Annual Survey of Manufactures (ASM) and the Current Population Survey (CPS). While CPS would seem to be the natural dataset for studying these issues since it includes wages, demographics, and (some) migration information, it has the drawback that the geographic detail can be rather coarse. In particular, it is only representative down to the state-level. On the other hand, the ASM allows us to study wage dispersion at any level of

[7]Housing prices may dampen unskilled migration for another reason: If they spend a higher fraction of their income on housing than skilled workers do (as has been shown in other work), then they are more sensitive to the higher housing prices in the destination region and less inclined to migrate. But we do not pursue this here.

geographic disaggregation (subject to confidentiality). Here we will take the county as the relevant unit of analysis. We would argue that this maps reasonably well into what we call a region in our model. The obvious drawback to the ASM is the fact that it only covers the manufacturing sector. While this sector represents only a relatively small share of the overall economy, it is a sector with a naturally high energy usage which differs widely across industries. Another advantage of the ASM is that it goes back to 1972 which covers the very large real oil price changes of the 1970s and 1980s.

3.1.1 Constructing wage measures

In the Annual Survey of Manufactures, the Census Bureau collects information on annual inputs and outputs of about sixty thousand establishments. This sample accounts for a large share of employment and output in the manufacturing sector. We use the data on labor compensation, employment, hours worked, fuels and output. The previous literature studied the impact of real oil price shocks on skilled and unskilled labor and our model follows that distinction. Our model implies differences in the response of wage dispersion to real oil price shocks across worker skill groups. To test these predictions, we map skilled labor into non-production workers and unskilled labor into production workers. Production workers comprise employees up to and including the line-supervisor level engaged in the core manufacturing activities such as fabricating, processing, assembling, inspecting, receiving, packing, warehousing, maintenance, repair, janitorial and guard services and record keeping. Non-production workers, in contrast, are employees above line-supervisor level which comprises executive, purchasing, professional and technical sales, logistics, advertising, credit, clerical and routine office functions. The lack of more detailed information about the skill content of labor is another limitation of the ASM. In the CPS, there is information on a person's level of education leading to clear definitions of skill.

Skilled wages are imputed by dividing the compensation of non-production workers by the number of non-production employees. For unskilled workers we compute wages per hour instead. This more refined measure takes into account part- and over-time work which is likely to be more prevalent for production workers. Below, we will also examine how an establishment's energy intensity shapes the effect of real oil price shocks on wages. We define energy intensity as the share of real fuel expenditures in real output. We could have chosen overall energy expenditures which we fear would not accurately reflect how an establishment is exposed to changes in the real oil price because it might substitute away to other energy sources. Fuels consist to a large extent of oil use. Finally, it is important to point out that this is an unbalanced panel of establishments and we make no attempt to correct for possible attrition bias.

3.1.2 Constructing a measure of oil supply shocks

We want to analyze the impact of changes in the real oil price on labor markets in the U.S. The obvious worry is the potential endogeneity of the real oil price (e.g. Kilian (2009); Barsky and Kilian (2002)) and wage dispersion. The worry is not that there is reverse causality from changes in dispersion to real oil price changes, but that there might be some third variable driving both dispersion and the real oil price. The most obvious such third variable is U.S. aggregate demand itself, which may directly affect wage dispersion and – because the U.S. economy is large – also global demand for oil and thus the real oil price. How can one extract the exogenous part of real oil price movements? The literature has developed several methodologies to extract the exogenous portion of real oil price movements driven by shocks to demand, supply, and speculation. We follow the methodology proposed by Kilian (2009) and construct a shock that drives the real oil price and is exogenous to U.S. manufacturing. This methodology decomposes real oil price movements into (1) oil supply shocks, (2) aggregate demand shocks and (3) oil-specific demand shocks. (1) captures unpredictable innovations to global oil production such as disruptions due to exogenous political events. (2) captures unpredictable innovations that raise global aggregate demand for all production inputs including oil which are unexplained by oil supply shocks. (3) captures unpredictable innovations that result in real oil price changes unexplained by both oil supply shocks and global aggregate demand shocks. As Kilian (2009) writes, these last innovation may be demand shocks for oil (relative to that for non-oil commodities) such as preference shocks or precautionary oil demand shocks.

We replicate Kilian's VAR for our slightly extended time period until 2015. A detailed description of our procedure and the data we use can be found in Appendix B. We focus on the effects of oil supply shocks (shock (1) above) since these shocks are most likely to be exogenous to the U.S. manufacturing sector. In our empirical work, we use the inverted time series of this shock so that positive innovations actually *increase* the real price of oil i.e. are negative supply shocks. For the remainder of the paper, we refer to these oil supply disruption shocks that raise the real price of oil as an "oil supply shocks." While Kilian (2009) finds the oil specific demand shock (3) to be an important driver of the real oil price, it is almost irrelevant in affecting the physical production of oil. The physical amount of oil available to the economy is mainly driven by exogenous oil supply shocks (1). We hence focus on this shock because it is the physical amount of oil which matters for real economic activity, labor demand and thus labor supply responses in our model.[8]

3.2 Oil supply shocks and wage dispersion

3.2.1 Constructing dispersion measures

We decompose the overall wage dispersion, skilled and unskilled, in the manufacturing sector into wage dispersion between counties and the average wage dispersion within a county:

$$\begin{aligned}\sigma &= \underbrace{\sum_n \omega_n (x_n - \overline{x})^2}_{\sigma \text{ overall}} \\ &= \underbrace{\sum_j \omega_j (x_j - \overline{x})^2}_{\sigma^B \text{ between county}} + \underbrace{\sum_j \omega_j \underbrace{\sum_n^{N_j} \tilde{\omega}_{jn} (x_{jn} - \overline{x}_j)^2}_{\sigma_j^W \text{ within county } j}}_{\sigma^W \text{ average within county}} \qquad (18)\end{aligned}$$

In the following, we focus on between-county dispersion σ^B as our main dependent variable. As Table 2 shows this between-county portion still represents a considerable share (up to a third) of overall wage dispersion. Furthermore, between-county

[8]To check for robustness, we also estimated our setup including oil specific demand shocks. But our results for the effects of oil supply shocks impact on skilled and unskilled wage dispersion are unaffected and the effect of oil specific demand shocks themselves are small and insignificant which is in line with the view that precautionary or preference shocks specific to oil demand have little impact on real activity at the annual frequency.

Table 2: Summary statistics

A. Moments of aggregate shocks	St. Dev. Oil supply shock			0.2636		
	St. Dev. Aggregate demand shock			0.3261		
B. Regional dispersion moments	Unweighted Moments			Weighted Moments		
	Average	Volatility over time		Average	Volatility over time	
		St. Dev.	CV		St. Dev.	CV
Dispersion of unskilled hourly wages						
Overall dispersion	0.1347	0.0204	0.151	0.15240	0.01589	0.10426
Between-county dispersion	0.0214	0.0048	0.223	0.05471	0.00766	0.14006
Average within-county dispersion	0.1133	0.0201	0.178	0.09797	0.01547	0.15787
Dispersion of skilled wages						
Overall dispersion	0.2024	0.0385	0.190	0.14739	0.03600	0.24427
Between-county dispersion	0.0192	0.0030	0.158	0.03344	0.00817	0.24436
Average within-county dispersion	0.1832	0.0360	0.197	0.11394	0.02838	0.24903
Dispersion of energy intensity						
Overall dispersion	3.39×10^{-5}	1.88×10^{-5}	0.556	0.00144	0.00097	0.67444
Between-county dispersion	0.34×10^{-5}	0.20×10^{-5}	0.590	0.00064	0.00045	0.71134
Average within-county dispersion	3.05×10^{-5}	1.69×10^{-5}	0.553	0.00080	0.00052	0.64833

Note: The oil supply shock is based on Kilian (2009) with a positive shock corresponding to a supply disruption, a higher real oil price and lower labor demand. By construction, the shock has mean zero. The overall dispersion of wages, $\log w$, and energy intensity, eq/y, is defined as the variance and is decomposed into the between-county dispersion of average wages/energy intensity and the average within-county dispersion of wages/energy intensity according to equation (18) for every year. This table displays the average dispersion component over the years (column "Average"), how much each component of dispersion fluctuates (columns "Volatility"). For economic relevance, this table displays wage dispersion weighted by employment and energy intensity dispersion weighted by energy use.

dispersion in energy intensity is almost half of the overall dispersion and though the share of fuels in output may be small, it is quite dispersed. Note that we weight establishment-level observations by labor input.

3.2.2 Oil supply shocks increase unskilled wage dispersion but have little impact on skilled wage dispersion

We regress various measures of wage dispersion based on different skill groups on contemporaneous and lags of the oil supply shock (keep in mind this is the structural shock to oil production resulting in an increase in the real oil price) as well as measures of aggregate economic activity and a time trend to control for any low frequency trends. Specifically, we estimate

$$\sigma_t^B = \beta_0 + \beta_1 t + \sum_{\tau=0}^{1} \delta_\tau^{Oil} Oil_{t-\tau} + \sum_{\tau=0}^{1} \delta_\tau^{Y} Y_{t-\tau} + \varepsilon_t \quad (19)$$

where σ_t^B is the between-county dispersion measure, Oil_t the estimated oil supply shock at time t and Y_t those unexpected aggregate demand fluctuations not driven by the oil supply shock at time t. Note that based on how the timing of the ASM a large share of wages is not measured until March of the following year. We account for that adjusting the time in wage dispersion. We run a version of equation (19) for both unskilled and skilled wage dispersion. We calculate both robust and Newey-West autocorrelation-robust standard errors allowing for one year of dependence. The Newey-West standard errors are reported in square brackets below the point estimates and display a similar magnitude as the ones obtained when clustering the standard errors at the year level. To emphasize, these regressions are run at the level of the US economy so there is only one observation per year.

The results for unskilled wages are reported in the left two columns of Table 3. We find fairly robust support for one implication of the theory. In column (I) where we study the unweighted wage dispersion between counties, the dispersion in unskilled wages increases sharply in the year after the shock. This is true in a statistical and economic sense with effects being significant at the 5% level. In interpreting the economic significance, Table 2 offers summary statistics for key independent and de-

Table 3: Effects of oil supply shocks on between-county wage dispersion

	(I)	(II)	(III)	(IV)
	Unskilled wage dispersion		Skilled wage dispersion	
	Unweighted	Weighted	Unweighted	Weighted
Y_t	-0.00252***	-0.00478**	-0.00494***	-0.00458**
	(0.000829)	(0.00217)	(0.00173)	(0.00207)
	(0.000775)	(0.00200)	(0.00192)	(0.00230)
Y_{t-1}	0.000658	-0.000984	-0.00311	-0.00422
	(0.000931)	(0.00214)	(0.00199)	(0.00252)
	(0.000951)	(0.00213)	(0.00219)	(0.00257)
Oil_t	0.00293***	0.00522***	0.00196	-0.002279
	(0.000848)	(0.00187)	(0.00148)	(0.00217)
	(0.000903)	(0.00194)	(0.00134)	(0.00200)
Oil_{t-1}	0.00243**	0.00301	0.00123	-0.000295
	(0.00111)	(0.00239)	(0.00178)	(0.00214)
	(0.00101)	(0.00229)	(0.00176)	(0.00204)
Observations	33	33	33	33
R^2	0.909	0.905	0.347	0.845

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Linear regression of dispersion of unskilled and skilled wages across counties (σ_t^B in equation (18)) on current and lagged measure of oil supply shocks (Oil_t) and controls. We include a linear time trend as well as current and lagged shocks to industrial output not driven by oil supply shocks (Y_t). Robust standard errors in parentheses and Newey-West standard errors with one lag are in brackets.

pendent variables. We note that unweighted between county wage dispersion makes about 16% of the total dispersion in unskilled wages and 9.5% for skilled wages; these shares are 36% and 22%, respectively, for employment weighted wage dispersion. Returning to the regression, we find that a typical oil supply shock increases unskilled wage dispersion by 3.6% of the mean on impact and is still 3.0% higher a year later. Statistical significance is unaffected if we use Newey-West standard errors reported in square brackets. In column (II), we redo the regressions using a dispersion measure where establishment observations are weighted by their production employment. Results are slightly weaker in this specification: the contemporaneous effect is 2.5% and 1.5% after a one-year lag. The coefficients in column (II) are more precisely estimated. In addition, our theory predicts that unskilled wage dispersion responds more strongly than skilled wage dispersion. So turning to the results for skilled wages reported in the right two columns of Table 3, we find that skilled wage dispersion is basically unaffected by either oil supply shocks or output shocks and almost always insignificantly different from zero. This conforms with our model prediction where skilled workers reallocate more quickly to benefit from higher wages elsewhere.

3.3 Changes in local labor supply and oil supply shocks

Our model shows that changes in wage dispersion for skilled and unskilled workers cannot be explained by labor demand adjustments alone. In particular, labor supply has to adjust in order to reconcile energy intensity differences across firms given the energy-skill complementarity suggested in the previous literature and empirically verified in an appendix. That is, we would expect workers, especially highly skilled ones, to migrate to regions where jobs are not as affected by a higher real oil price. To that end, we now present direct empirical evidence on the impact of oil supply shocks on the reallocation of workers across regions using the CPS.[9] Like the establishment-level data from the ASM/CMF, this is an annual survey spanning the same time horizon (and more) covering a large set of workers, their socio-economic characteristics and – importantly – their location and whether they changed location since the last year. The migration information is missing in some years when the agency decided

[9]The data come from King et al. (2010) and can be downloaded from `https://cps.ipums.org/cps-action/variables/group`.

to sample migration from 5 years ago instead of one year ago.

It is important to make clear the timing of the CPS migration data. The CPS provides information on the MSA a person currently resides in at year t and asks retrospectively if whether they moved from a different county (or state) in year $t-1$. For the timing of effects, this means that we expect oil supply shocks at year $t-1$ to drive migration decisions in year $t-1$, which will appear in CPS at year t after people have relocated. We account for the non-standard timing of migration in the CPS data in our regression analysis below.

The CPS does not provide information on whether the person was living before if they moved. So we are not able to identify if they moved from, say, a very energy intensive region. We can only identify if they *immigrated to*, say, an energy intensive region.

3.3.1 Oil supply shocks increase spatial worker reallocation

We begin by studying the between-state and between-county migration of workers in general by estimating a probit model as a function on the oil supply shocks and other observables:

$$Migrant_{it} = 1\left[\beta_1 t + \sum_{\tau=0}^{1} \delta_\tau^{Oil} Oil_{t-\tau} + \sum_{\tau=0}^{1} \delta_\tau^{Y} Y_{t-\tau} + X_{it}'\gamma > \varepsilon_{it}\right] \tag{20}$$

where X_{it} is a vector of individual demographics influencing a migration decision other than oil supply shocks.

Since migration likely depends on local living expenses and since a large share of local living costs are related to the elasticity of housing supply, we use housing supply estimates produced by Saiz (2010) to account for this.[10] In particular, we will run regression (20) separately for MSAs with a high versus low housing supply elasticity. We classify a MSA as having a high housing supply elasticity when its elasticity is above the median estimate from Saiz of 2.26 and vice versa if it is below the median. We classify all rural areas as having a high-housing supply elasticity even though Saiz did not calculate values for this group.

[10]We are very grateful to Albert Saiz for making his full dataset available to us.

Lastly, we include a host of socio-economic controls that have been found to matter for migration decisions (see notes to Table 4) and we consider both inter-state and inter-county migration. We include the between-state migration as an additional robustness check even though our geographic unit of analysis in the wage dispersion regressions was the county.

Before discussing the magnitude of the results, it is important to keep in mind the interpretation of these marginal effects. Because this is a non-linear model, it matters at which values of the explanatory variables the effect is calculated from. The standard in the literature, which we follow, is to evaluate at the means of the explanatory variables. However, these means will differ in general across the specifications. High housing supply elasticity MSAs may have different average demographics of people living there than low supply elasticity MSAs. For this reason, we also estimated simple linear regressions (omitted here, but available upon request) for which the marginal effect is independent of the point at which it is evaluated. These regressions of course are misspecified since the dependent variable is binary. However, the interpretation is clearer and the local effect is far from implying migration probabilities larger than unity. We find results of similar magnitude to those using the probit.

Table 4 shows that there is increased migration in response to an oil supply shock that increases the real price of oil. The effects are highly statistically and economically significant across all specifications and subsamples including both between-state and between-county migration. In particular, we find that a positive one standard deviation oil supply shock in the previous year increases between state-migration by about 0.49% for high housing supply elasticity regions. Relating this effect to the baseline migration rate of 2.0%, this means that a typical oil supply shock increases migration into a state by about a quarter. In low housing supply elasticities, the baseline migration rate of 1.8% increases only by 0.26% (about a fifth) in the wake of a typical oil supply shock. These differences across regions as a function of housing supply elasticity accords with the model and the role of local non-tradeables. The absolute effects are even stronger for between-county migration – almost double the state-level results – but are similar relative to their long-run means: a typical oil supply shock increases migration into counties by a fifth and a quarter, respectively. One slightly surprising result is that longer lags of the oil supply shock still affect

Table 4: Migration and oil supply shocks

Panel A. Between-state migration

	(I)	(II)	(III)	(IV)
Oil_t	0.364***	0.208***	0.312***	0.189***
	(0.0319)	(0.0522)	(0.0332)	(0.0522)
	[0.49%]	[0.26%]	[0.41%]	[0.24%]
Oil_{t-1}	0.232***	0.115**	0.202***	0.0987**
	(0.0289)	(0.0497)	(0.0315)	(0.0499)
	[0.31%]	[0.15%]	[0.26%]	[0.13%]
HSE	high	low	high	low
Weights	none	none	CPS	CPS
N	2,333k	1,632k	2,333k	1,632k

Panel B. Between-county migration

	(I)	(II)	(III)	(IV)
Oil_t	0.394***	0.236***	0.346***	0.207***
	(0.0298)	(0.0481)	(0.0347)	(0.0496)
	[0.93%]	[0.54%]	[0.86%]	[0.51%]
Oil_{t-1}	0.216***	0.111**	0.182***	0.0906*
	(0.0267)	(0.0460)	(0.0326)	(0.0490)
	[0.51%]	[0.25%]	[0.45%]	[0.22%]
HSE	high	low	high	low
Weights	none	none	CPS	CPS
N	2,333k	1,632k	2,333k	1,632k

Standard errors in parentheses, marginal migration propensities after typical oil supply shock in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Probit regression of migration on oil supply shocks and controls as laid out in equation (20). We include a linear time trend, economic controls – education level, income and industry dummies – and social controls – age, sex, marital status, dummies for racial subgroups. Standard errors in parentheses below the estimates are clustered at the year-state level; numbers in brackets are the marginal effects on the migration probability in percentage points of a one-standard deviation oil supply shock. $Oil_{t-k}, k = 0, 1$ refers to the exogenous oil supply shock measure we estimate in Section 3.1.2. These also include the (non-oil) output shocks from above. Columns (I) and (III) each run the Probit in regions with a high housing supply elasticity (HSE "high") as estimated by Saiz (2010); columns (II) and (IV) in regions with a low housing supply elasticity (HSE "low"). Specifications (III) and (IV) use CPS weights to account for the sampling frame.

migration decisions. Oil supply shocks with a one-year lag still affect migration with a slightly smaller magnitude than the one year lagged shocks. The results using the weights are very similar to the unweighted ones in terms of both statistical and economic significance.

3.3.2 Skilled workers are more responsive to oil supply shocks

Our model predicts that skilled migration is more sensitive to oil supply shocks than unskilled migration. To test these implications, we run a set of probit regressions separately for skilled and unskilled workers. Following the literature, we define unskilled labor as workers with an associate's degree after finishing an occupational/vocational program or less education. Skilled workers are those with more than two years of college or a higher academic grade though we also experiment with skilled workers possessing a bachelor's degree or more.

The resulting estimates and migration propensities are displayed in Table 5. Indeed, skilled workers are more likely to migrate. The magnitude of these effects appears to be monotonically increasing in skill (though there is not much difference between the skilled and the very skilled groups). Like the earlier probit results, it is important to keep in mind that these marginal effects are implicitly being evaluated at different points as the average demographics differ across the skill groups. And as before, the effects of oil supply shocks are strongest in regions with above the median housing supply elasticities, an intuitive result. Also like the basic migration regressions, the effects are substantially stronger for between-country migration.

3.3.3 Workers reallocate to energy non-intensive regions

The third main prediction of the model is that migration should not only be triggered by increases in the oil supply shocks but that it is directed *towards* regions that are not as energy intensive. Assessing this prediction requires matching regional information on energy intensity from the ASM with the migration behavior of workers from the CPS. Disclosing average energy intensity by county and year violates Census disclosure requirements, so we have to aggregate counties to metropolitan statistical areas (MSAs) which are also available in the CPS. We classify each MSA into energy

Table 5: Skilled vs. unskilled migration and oil supply shocks

Panel A. Between-state migration

	(Ia)	(Ib)	(Ic)	(IIa)	(IIb)	(IIc)
Oil_t	0.338^{***}	0.336^{***}	0.374^{***}	0.206^{***}	0.195^{***}	0.215^{***}
	(0.0350)	(0.0334)	(0.0335)	(0.0570)	(0.0556)	(0.0555)
	[0.60%]	[0.57%]	[0.46%]	[0.35%]	[0.32%]	[0.24%]
Oil_{t-1}	0.208^{***}	0.205^{***}	0.243^{***}	0.112^{**}	0.112^{**}	0.118^{**}
	(0.0323)	(0.0302)	(0.0308)	(0.0558)	(0.0534)	(0.0519)
	[0.37%]	[0.35%]	[0.30%]	[0.19%]	[0.18%]	[0.13%]
Skill level	very skilled	skilled	unskilled	very skilled	skilled	unskilled
HSE	high	high	high	low	low	low
N	429k	562k	1,772k	397k	493k	1,138k

Panel B. Between-county migration

	(Ia)	(Ib)	(Ic)	(IIa)	(IIb)	(IIc)
Oil_t	0.385^{***}	0.373^{***}	0.401^{***}	0.230^{***}	0.224^{***}	0.241^{***}
	(0.0327)	(0.0311)	(0.0309)	(0.0488)	(0.0475)	(0.0507)
	[1.09%]	[1.03%]	[0.89%]	[0.64%]	[0.61%]	[0.50%]
Oil_{t-1}	0.195^{***}	0.186^{***}	0.227^{***}	0.111^{**}	0.107^{**}	0.113^{**}
	(0.0300)	(0.0283)	(0.0277)	(0.0479)	(0.0465)	(0.0476)
	[0.55%]	[0.51%]	[0.50%]	[0.31%]	[0.29%]	[0.23%]
Skill level	very skilled	skilled	unskilled	very skilled	skilled	unskilled
HSE	high	high	high	low	low	low
N	428k	562k	1,772k	397k	493k	1,138k

Standard errors in parentheses, marginal migration propensities after typical oil supply shock in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Probit regression for migration decision of very skilled, skilled and unskilled workers in response to oil supply shocks. “Very skilled” are workers with a bachelor’s degree or more, “Skilled” are those with at least two years of college, “Unskilled” are those with an associate’s degree or less. All regressions are unweighted. For further details on controls, etc., see notes to Table 4.

intensity quartiles and define a MSA as low energy intensity if its share of energy less electricity expenditures in gross output is in the lowest quartile of energy intensity across all MSAs in any given year. High energy intensity is the complement. Of course, we are mindful that oil represents only a portion of overall energy expenditures which we unfortunately do not observe separately from other energy inputs in the ASM data. However, we verified that at the annual frequency of our analysis the prices of most energy inputs – oil, coal, coke and natural gas – comove strongly; the only exception is electricity which we fortunately do observe separately and thus exclude from our measure of energy intensity.

We estimate where the direction of worker migrate as a function of energy intensity in response to oil supply shocks. It is important again to keep in mind the information on migration reported on the CPS. The survey reports where a person was living in year t and asks the person to report if he lived there in year $t-1$. What this means is that we can observe whether migration rates *into*, say, low energy intensity regions are higher after a negative oil supply shock, but we cannot observe if those people moved from, say, high energy intensity regions.

Table 6 show that indeed, in-migration into MSAs with a low energy intensity is quite pronounced after oil supply shocks while in-migration into MSAs with a high energy intensity is much weaker. Finally, we study if directed migration into energy efficient MSAs is particularly strong among skilled workers compared to unskilled workers. The model predicted that skilled workers have a higher incentive to reallocate to energy efficient regions than unskilled workers. So we split the set of in-migration into MSAs with a low energy intensity into subgroup of very skilled (bachelor's degree or more) and unskilled workers (associate's degree or less). The results from these split-sample probit regression are displayed in columns (IIa) through (IIc). The results show that this change in inflows is driven by changes in the composition of who immigrates towards the higher skilled. Finally, Panel B redoes these probits for inter-county migration finding slightly stronger effects across all the various specifications though with the same orderings across skill groups and regional energy intensity.

Table 6: Regionally directed migration and oil supply shocks

Panel A. Between-state migration

	(Ia)	(Ib)	(IIa)	(IIb)	(IIc)
Oil_t	0.415***	0.139***	0.393***	0.391***	0.423***
	(0.0345)	(0.0467)	(0.0385)	(0.0367)	(0.0362)
	[0.60%]	[0.25%]	[0.80%]	[0.77%]	[0.51%]
Oil_{t-1}	0.272***	0.0181	0.251***	0.248***	0.280***
	(0.0304)	(0.0512)	(0.0351)	(0.0326)	(0.0322)
	[0.60%]	[0.25%]	[0.80%]	[0.77%]	[0.34%]
Energy intensity	low	high	low	low	low
Skill level	all	all	very skilled	skilled	unskilled
HSE	high	high	high	high	high
N	1,852k	481k	323k	427k	1,425k

Panel B. Between-county migration

	(Ia)	(Ib)	(IIa)	(IIb)	(IIc)
Oil_t	0.447***	0.179***	0.445***	0.429***	0.453***
	(0.0313)	(0.0424)	(0.0352)	(0.0334)	(0.0323)
	[1.02%]	[0.47%]	[1.22%]	[1.15%]	[0.98%]
Oil_{t-1}	0.260***	-0.0160	0.246***	0.232***	0.269***
	(0.0273)	(0.0493)	(0.0314)	(0.0294)	(0.0283)
	[0.59%]	[-0.04%]	[0.67%]	[0.62%]	[0.58%]
Energy intensity	low	high	low	low	low
Skill level	all	all	very skilled	skilled	unskilled
HSE	high	high	high	high	high
N	1,852k	481k	323k	427k	1,425k

Standard errors in parentheses, marginal migration propensities after typical oil supply shock in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Probit regression for migration decision of skilled and unskilled workers in response to oil supply shocks towards energy non-intensive (columns (Ia), (IIa)-(IIc)) versus energy intensive (column (Ib)) MSAs. An energy non-intensive MSA means that the share of energy consumption in output is in the bottom quartile; energy intensive refers to the complement. For details on controls etc. see notes to Table 4.

3.4 Oil supply shocks and housing prices

Our model also makes predictions for the response to oil supply shocks of the prices of local non-tradeables. To study this, we use data on the housing value collected by Davis and Palumbo (2008). It is important to keep a few caveats in mind. First, this housing price series goes back to 1984 and covers only 46 large MSAs (though not all are there for all the years). In addition, housing is only one part (though a large one) of the overall non-tradeable budget of a household. With all those caveats in mind, we estimate

$$\log r_{it} = \beta_0 + \beta_1 t + \sum_{\tau=0}^{1} \delta_\tau^{Oil} Oil_{t-\tau} + \sum_{\tau=0}^{1} \delta_\tau^{Y} Y_{t-\tau} + \sum_{\tau=0}^{1} \omega_\tau \chi_{it} Oil_{t-\tau} + \sum_i \psi_i MSA_i + \varepsilon_{it} \tag{21}$$

where the only difference with the previous regressions is the inclusion of a full set of MSA fixed effects, $\sum_i \psi_i MSA_i$. We also treat the housing supply elasticity, denoted by χ, as a continuous variable rather than an indicator for being above or below the median housing supply elasticity. As in the migration regressions in the previous subsections, we group MSAs by their energy intensity and separately estimate equation (21) for energy efficient and energy intensive MSAs. We are limited by the size of the dataset in what we can include as additional controls such as MSA specific time trends. We cluster standard errors at the year-level and weight MSAs by their 2000 population.

Our findings are reported in Table 7. When pooling all MSAs – energy efficient and energy intensive ones – the current oil supply shock has an insignificant effect on impact, but the lagged effect is a decline of 1.6% when evaluating at the median housing supply elasiticity.

In columns (IIa) and (IIb) we estimate equation (21) separately for MSAs with low (lowest quartile) and high (highest three quartiles) energy intensity. This shows that housing price response differs across MSAs according to their energy intensity which is obscured in the pooled regression. As expected, housing prices fall in MSAs with a high energy intensity which are abandoned by workers. The lower housing demand suppresses housing prices. Column (IIb) shows that housing prices in energy intensive MSAs fall and this effect persists for another year. The housing prices change

Table 7: Effects of oil supply shocks on housing prices

	(I)	(IIa)	(IIb)	(IIIa)	(IIIb)
Oil_t	0.0740	0.118	0.0642	0.0245	0.0889
	(0.0452)	(0.0788)	(0.0554)	(0.0773)	(0.0561)
Oil_{t-1}	-0.141***	-0.0859	-0.155***	-0.196***	-0.154***
	(0.0425)	(0.0752)	(0.0516)	(0.0742)	(0.0525)
$\chi \times Oil_t$	-0.0153	-0.0317	-0.0109	0.000658	-0.0125
	(0.0248)	(0.0371)	(0.0327)	(0.0401)	(0.0376)
$\chi \times Oil_{t-1}$	0.0672***	0.0471	0.0674**	0.0891**	0.0738**
	(0.0232)	(0.0352)	(0.0306)	(0.0384)	(0.0352)
Energy Intensity	all	low	high	low	high
N	1,144	339	805	339	805
R^2	0.874	0.834	0.870	0.834	0.875

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Regressions of log local housing prices on oil supply shocks as laid out in equation (21). All regressions include an aggregate linear time trend, MSA fixed effects and (non-oil) output shocks. Note that the housing data source from Davis and Palumbo (2008) only goes back to 1984 and only covers 46 MSAs. Standard errors are clustered at the year-level and reported in parenthesis.

insignificantly on impact and decline by 1.44% a year later. In low-energy intensity MSAs, in contrast, price changes are always insignificant. Using MSA population weights (see columns (IIIa) and (IIIb)) gives slightly stronger but qualitatively similar results. All these effects are calculated using the median housing supply elasticity for the particular set of MSAs considered in the regression.

4 Quantitative Analysis

The estimated responses of wages and spatial labor reallocation in the previous section confirmed the theoretical predictions of the model presented in Section 2. The empirical estimates also revealed that oil supply shocks have a significant impact on wages and migration overall. We now want to link the two previous sections and quantify the contribution of the model mechanism to the empirically estimated responses of oil supply shocks. To do this, we need to link the oil supply shocks to the induced effects on real oil prices. To that end, we calibrate our model and simulate a real oil price shock of the magnitude observed in the data induced by an oil supply shock.

4.1 Calibration

We choose model the model parameters $\alpha, \theta, \beta, \gamma_i, \gamma_j, \overline{q}$ to match salient moments in our data. Table 8 displays our calibration and their targeted data moments. The γ's and α can be calibrated using data from the Annual Survey of Manufactures which underlies our empirical analysis of wages and wage dispersion. By using the same data for the empirical analysis and the calibration we provide a close link between our quantitative and empirical analysis.

The elasticity of unskilled labor in the model, α, corresponds to the expenditure share of unskilled wages in total costs in any region: $\alpha = \frac{w^u u}{w^u u + w^s s + qe}$. As before, we identify the unskilled wage bill with expenditures for production labor and that for skilled workers with expenditures for non-production labor; energy cost comprise energy expenditures. We compute the sums for each of these expenditures across the ASM by year, compute the ratio of these to obtain an annual value for α and then

Table 8: Calibration

Parameter	Definition	Value	Source/Target
α	production elasticity unskilled labor	0.58	share of unskilled wage bill in total labor and energy costs in ASM
γ_i	inverse energy intensity in region i	0.141	ratio of skilled labor to energy inputs in energy efficient counties in ASM
γ_j	inverse energy intensity in region j	0.025	ratio of skilled labor to energy inputs in energy inefficient counties in ASM
β	inverse housing supply elasticity	0.763	median value of Saiz (2010), Table VI, matched in the housing data
θ	housing weight in unskilled utility	0.44	share of non-tradables in CPI basket, Source: Bureau of Labor Statistics (2007), Ch. 7, App. 4.
q	long-run real oil price	0.00187	regional dispersion of energy expenditures in value added in the ASM

compute the average across all years which yields a value of 0.58.

Next, we direct attention to differences in energy intensity across regions. This is jointly regulated by the γ's and the real oil price, q, which is denoted in terms of final output. Give the complementarity between oil and skilled labor in our production function, γ is reflected in the ratio of skilled labor, s, to energy input, e. Targeting this moment has the advantage that it is measured very easily; alternatives to calibrate γ such as the energy intensity depend on prices for other factors such as unskilled labor and labor supply and housing supply parameters. In the data, we classify regions according to their energy intensity for every year as in the empirical work. For each group and year we then compute the aggregate level of non-production labor and energy inputs deflated by the industry-year specific energy price index from the NBER-CES manufacturing database and take the ratio. Then, we average across years to get the typical energy intensity in high- and low- intensity regions at 0.025 and 0.141, respectively. Of course, the γ's will also determine the level of skilled and unskilled wage dispersion in our model, but we do not use wage dispersion as a calibration target because a plethora of factors beyond energy prices will influence that level. Instead, we will rather examine the *relative response* of wage dispersion to real oil price shocks in the calibration and compare that to the empirical response outlined in Table 3. Given our calibration for the γ's, we choose the real oil price $q = 0.00187$ in order to match the between-county variance of energy usage in output across the same high-versus low-energy intensity regions listed in Table 2.

Two parameters remain which need to be calibrated from outside data sources. The inverse housing supply elasticity, β, regulates how quickly housing prices will rise following in-migration of workers; many factors affect that parameter such as regulation and zoning laws, geographical constraints and other factors affecting the construction of new housing. Saiz (2010) has estimated these housing supply elasticities containing many of these factors for each MSA in the U.S. We pick the average value from his estimates that we can match to our CPS and housing data. This corresponds to the housing supply elasticity of 1.31 (roughly that of Las Vegas, NV), i.e. a value for our $\beta = 1/1.31 \approx 0.763$.

Lastly, we need to calibrate the value for θ which reflects the elasticity of utility with respect to locally purchased housing, h. All other household expenditures in our model are spent on tradable consumption goods, c. We turn to the consumer price index by the BLS and classify the underlying basket into tradable and non-tradable goods. We classify that Fuels & Household Equipment, Gasoline & Fuel, Other Transportation expenses, Food & Beverages, Apparel as tradables while Shelter, Utilities and Public Transport are non-tradable.[11] Computing the share of non-tradable expenditures in total expenditures, we set θ to 0.44.

4.2 Responses

We now consider a typical oil supply shock used in the empirical sections. The impulse response of the real price of oil to such a typical oil supply shock corresponds to an increase in the first year of about 1.7%. Exogenously increasing the real oil price in our model by that amount delivers a response of wages, wage dispersion, increased spatial allocation in low-energy intensity regions and housing prices. Column (I) in Table 9 reports the empirical reduced-form estimates. Columns (IIa) and (IIb) report

[11] We omit other categories such as Recreation, Education and Medical Care which are more ambiguous in their tradability.

the quantitative response of our model after a “typical” and a “large” real oil price shock. The latter shock represents the largest disruption shock in our sample which occurred in 1980 and is more than three times as strong as a typical shock.

Our model captures a fair share of the wage levels and the relative responses across skill groups and regions. Skilled wages in the energy intensive region, for example, drop by about a fifth of the empirically estimated wage level. For a large shock such as the one in 1980 our model generates over 80% of the overall response. Wages in the other skill group and region show similar patterns. The model wage response in the energy efficient regions underestimates those in the data: skilled wages drop only half as much and unskilled wages more or less stagnate. This is because unskilled workers in the model’s energy efficient region benefit from skilled in-migration which makes them more productive.

Wage dispersion across regions responds more strongly for unskilled than skilled labor in the data. This was also true for the linear approximation of the model as described in Proposition 2.5. In the non-linear response of the model which we consider in this quantitative analysis, this need not necessarily be true. It turns out, however, that unskilled dispersion does respond more strongly than skilled wage dispersion. The latter increases only by 2.5% more than the former. We would note that the model overshoots the estimated percentage changes in wage dispersion for both groups while getting the differential change right. This seems to be an artifact of the limited sources of dispersion in the first place. Wages can only differ for workers of the same skill group because of differences in energy intensity across regions. Again, a large shock can explain about two thirds of the empirically estimated relative wage dispersion response. We emphasize that the sign of the relative wage dispersion response would be negative if there was no labor reallocation across regions.

Then, we consider the spatial reallocation response in our model and compare it to the estimated response in the data. The migration propensity of skilled labor increased by 1.2%, that of unskilled labor by less than 1.0%. Our calibration suggests that 0.6% of the skilled population in the energy efficient region migrated in after a real oil price shock; this number comes out at 0.4% for unskilled workers. A typical real oil price shock induced by an oil supply shock in the model thus explains less than half of each skilled and unskilled migration, but a large real oil price shock brings the

Table 9: Quantitative effects of real oil price shocks

Variable	Data	Model	
		Typical shock	Large shock
	(I)	(IIa)	(IIb)
$\Delta \log(w_i^u)$	-0.4%	$+0.0\%$	$+0.1\%$
$\Delta \log(w_j^u)$	-0.6%	-0.1%	-0.3%
$\Delta \log(w_i^s)$	-0.9%	-0.1%	-0.4%
$\Delta \log(w_j^s)$	-1.1%	-0.2%	-0.9%
$\Delta \log V(w^u) - \Delta \log V(w^s)$	$+2.5\%$	$+0.4\%$	$+1.5\%$
Δs_i	$+1.2\%$	$+0.6\%$	$+2.0\%$
Δu_i	$+1.0\%$	$+0.4\%$	$+1.3\%$
$\Delta \log r_j - \Delta \log r_i$	-1.4%	-0.3%	-1.0%

Note: Data effects come from regressions reported earlier in the text, see Tables 3, 6 and 7 as well as additional evidence in Table 10. A "normal shock" is a one standard deviation shock to the exogenous oil supply, a "large shock" refers to the largest estimated value for the oil supply disruption shock measure which occurred in 1980.

response just above the empirical estimate.

Next, we examine the effect in our model on housing prices relative to our regression estimates. In particular, we feed in the typical real oil price shock induced by our estimated typical oil supply shock into the column (II) of Table 7 to estimate the change in housing prices across these regions. Like with wage dispersion, a myriad of factors other than the real oil price and not considered in the empirical analysis or the model will impact the dynamics of housing prices. We therefore aim at the relative response of housing prices across regions with high or low energy intensity. Overall, a "normal shock" our model generates a relative housing price decline of 0.3% which is about a fifth of the empirically observed decline. The higher the migration rates, the larger the housing price divergence. As described above, we explain half of the migration rates with a typical shock. But a large shock in our model fully explains the empirical migration response and thus brings the response of housing prices up to over two thirds of the empirically observed 1.4% relative housing price decline.

Our model mechanism can thus explain between a fifth and two thirds of the empirically observed responses to wages, wage dispersion, migration and housing prices if we simulate a "typical" 1.7% real oil price shock. It should be noted that there are shocks as large as more than three times that of a "typical" real oil price shock. Column (IIb) in Table 9 thus displays the response of such a shock to the model. Due to the non-linear nature of the model, the responses for some variables are slightly weaker than three times those to a normal shock while others such as wage dispersion are stronger. Such a shock brings most variables closer to the empirical estimates and even overshoots in explaining a few variables. We thus conclude that a mixture of "typical" and "large" real oil price shocks is well in line with the quantitative predictions of the empirical estimates and that our model mechanism is indeed quantitatively relevant.

5 Conclusion

We have established a new stylized fact: negative oil supply shocks that increase the real oil price and the dispersion of unskilled wages are positively correlated. While existing research has focused on explaining the response of the aggregate wage level or the skill premium, we provide a model that can match both the level and the higher moments of wages between and within skill groups. In our model, firm differences in energy intensity lead to an asymmetric response of labor demand driving up wage dispersion. In a world with perfect labor markets and homogeneous living expenses labor reallocation would offset this wage dispersion. Because of local non-tradeables, real oil price shocks induce strong reallocation of skilled workers, which limits the response of skilled wage dispersion. Unskilled workers, in contrast, migrate much less because they benefit from externalities of skilled migration in terms of lower local living expenses. This leads to a relatively large increase in the dispersion of unskilled wages.

Going forward, much more can be learned about the interaction between local labor demand and supply. Here we showed how the dynamics of higher-order moments can be useful for identification purposes. While labor demand operates in a specific way that should affect the levels and dispersion of wages in the same way, labor supply movements alters the picture on wage dispersion. In this way, using information on the joint dynamics of first and second moments of wages helps to tell apart labor demand and supply disturbances otherwise confounded in average wages.

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A Proofs

Proof of Proposition 2.1 We can calculate

$$\frac{\partial SP}{\partial q} = -\frac{1}{\alpha\gamma_i}\left(\frac{s_i}{u_i}\right)^{\alpha-1} < 0$$
$$\frac{\partial V(w^s)}{\partial q} = 2s_i s_j (w_i^s - w_j^s)\left(\frac{\gamma_i - \gamma_j}{\gamma_i\gamma_j}\right).$$

For the second part of the proposition, with differences in γ the downward shift in skilled labor demand in energy-efficient regions (high γ) will be less pronounced than in energy-inefficient regions. Holding labor supply fixed this means that skilled wages across regions would become more dispersed ($|w_i^s - w_j^s|$ increases) if originally $w_i^s > w_j^s$ and less dispersed ($|w_i^s - w_j^s|$ decreases) if originally $w_i^s < w_j^s$. Finally, in contrast to skilled wage dispersion, unskilled wage dispersion does not change at all because the demand curve for unskilled labor does not change as one can see from equation (2). $\blacksquare$

Proof of Proposition 2.2 First note that $\tilde{s}_i > \tilde{s}_j \Leftrightarrow s_i > u_i \Leftrightarrow \frac{s_i}{u_i} = \tilde{s}_i > 1$. Now we prove that $\tilde{s}_i > \tilde{s}_j$. Assume otherwise, i.e. $\tilde{s}_i < 1 < \tilde{s}_j$, then the no-migration condition, equation (14), does not hold: If $\tilde{s}_i < \tilde{s}_j$, then the LHS is smaller than 1, but the RHS is greater than 1. To see the latter, note that $\tilde{s}_i < \tilde{s}_j \Leftrightarrow \tilde{s}_i^{-\alpha} > \tilde{s}_j^{-\alpha}$. Because we assumed region i to be more energy-efficient, $\gamma_i > \gamma_j \Leftrightarrow \frac{-q}{\gamma_i} > \frac{-q}{\gamma_j}$. Thus, both terms in the numerator of the RHS are greater than the analogous terms in the denominator, so the RHS is greater than 1.

Substituting this result into equation (2) shows that $w_i^u > w_j^u$. Equation (12) delivers the result for housing prices and equation (13) the result for skilled wages. $\blacksquare$

Proof of Proposition 2.3 We take a linear approximation about $\tilde{s}_j = \tilde{s}_i = 1$ to equations (14) and (15):

$$\frac{q}{\gamma_i} + \frac{1-\alpha}{\tilde{\theta}\omega_i}(\tilde{s}_i - 1) = \frac{q}{\gamma_j} + \frac{1-\alpha}{\tilde{\theta}\omega_j}(\tilde{s}_j - 1)$$
$$-\omega_i(\tilde{s}_i - 1) = \omega_j(\tilde{s}_j - 1)$$

Note that $\omega_k > 0$ for all k by our technical assumption on parameters and the real oil price. Solving these two linear equations delivers the result. $\blacksquare$

Proof of Proposition 2.4 We differentiate equation (16) with respect to the real oil price. Note that $\omega_i < \omega_j$ and that $\omega_k' \equiv \frac{\partial \omega_k}{\partial q} = \frac{1}{\gamma_k}\omega_k^2 > 0$.

$$
\begin{aligned}
\frac{\partial \tilde{s}_i}{\partial q} &= \frac{\tilde{\theta}\left(\frac{1}{\gamma_j}-\frac{1}{\gamma_i}\right)}{1-\alpha}\left\{\frac{\omega_i\omega_j^2}{\omega_i^2+\omega_j^2}+q\left[\frac{(\omega_i^2+\omega_j^2)(\omega_j^2\omega_i'+2\omega_i\omega_j\omega_j')-2\omega_i\omega_j^2(\omega_j\omega_j'+\omega_i\omega_i')}{\left(\omega_i^2+\omega_j^2\right)^2}\right]\right\} \\
&= \frac{\tilde{\theta}\left(\frac{1}{\gamma_j}-\frac{1}{\gamma_i}\right)}{1-\alpha}\left\{\frac{\omega_i\omega_j^2}{\omega_i^2+\omega_j^2}+q\left[\frac{2\omega_i^3\omega_j\omega_j'+\omega_j^2\omega_i'\left(\omega_j^2-\omega_i^2\right)}{\left(\omega_i^2+\omega_j^2\right)^2}\right]\right\} \\
&= \tilde{s}_i\left[\frac{1}{q}+\frac{2\gamma_i\omega_i^2\omega_j+\gamma_j\omega_i(\omega_j^2-\omega_i^2)}{\gamma_i\gamma_j(\omega_i^2+\omega_j^2)}\right] > 0.
\end{aligned}
$$

Now totally differentiating $\tilde{s}_i$ implies

$$
\begin{aligned}
\frac{d\tilde{s}_i}{dq} &= \frac{d\left(\frac{s_i}{u_i}\right)}{dq} = \frac{1}{u_i}\left[ds_i - \frac{s_i}{u_i}du_i\right] \\
&\Rightarrow \frac{ds_i}{dq} > \frac{du_i}{dq}
\end{aligned}
$$

For the skill intensity in region j we totally differentiate this expression

$$
\begin{aligned}
\frac{d\left(\frac{1-s_i}{1-u_i}\right)}{dq} &= \frac{-1}{1-u_i}\frac{ds_i}{dq} + \frac{1-s_i}{(1-u_i)^2}\frac{du_i}{dq} \\
&= \frac{-1}{1-u_i}\left[\frac{ds_i}{dq} - \frac{1-s_i}{1-u_i}\frac{du_i}{dq}\right]
\end{aligned}
$$

Because $\frac{1-s_i}{1-u_i} < 1$ and $\frac{ds_i}{dq} > \frac{du_i}{dq}$ we know that the term in the brackets is strictly positive, thus the entire expression negative, so that $\frac{\partial \tilde{s}_j}{\partial q} < 0$. ∎

Proof of Proposition 2.5 Recall the expression for unweighted and weighted wage dispersion

$$
\begin{aligned}
w_i^u - w_j^u &= \alpha\left(\tilde{s}_i^{1-\alpha} - \tilde{s}_j^{1-\alpha}\right) \\
V(w^u) &= u_i(1-u_i)(w_i^u - w_j^u)^2
\end{aligned}
$$

Note that for $q = 0$ both unweighted and weighted wage dispersion are nil. From Proposition 2.4 we know that $\frac{\partial \tilde{s}_i}{\partial q} > 0$ and $\frac{\partial \tilde{s}_j}{\partial q} < 0$, so the unweighted wage dispersion across regions rises. This also pushes up weighted wage dispersion.

For simplicity we show that in the approximation $\frac{\partial \log[V(w^u)]}{\partial q} > 0$. Because the logarithm is monotone transformation, this implies that $V(w^u)$ itself is increasing in the real oil price as well.

$$\log[V(w^u)] = \log[u_i(1-u_i)] + 2\log(\tilde{s}_i^{1-\alpha} - \tilde{s}_j^{1-\alpha}) + 2\log\alpha$$

We plug in the expressions for $u_i = \frac{1-\tilde{s}_j}{\tilde{s}_i-\tilde{s}_j}$ and $1-u_i = \frac{\tilde{s}_i-1}{\tilde{s}_i-\tilde{s}_j}$ and linearly approximate the second term around $\tilde{s}=1$: $\tilde{s}^{1-\alpha} = 1 + (1-\alpha)(\tilde{s}-1)$, then this proposition is equivalent to showing that

$$\begin{aligned}\frac{\partial V(w^u)}{\partial q} &= \frac{\partial}{\partial q}\left[\log(\tilde{s}_i - 1) + \log(1-\tilde{s}_j) - 2\log(\tilde{s}_i - \tilde{s}_j) + 2\log(1-\alpha) + 2\log(\tilde{s}_i - \tilde{s}_j) + 2\log\alpha\right] \\ &= \frac{\partial\tilde{s}_i/\partial q}{\tilde{s}_i - 1} - \frac{\partial\tilde{s}_j/\partial q}{1-\tilde{s}_j}\end{aligned}$$

From Proposition 2.2 we know that $\tilde{s}_i > 1 > \tilde{s}_j$ and from Proposition 2.4 we know that $\frac{\partial\tilde{s}_i}{\partial q} > 0$ and $\frac{\partial\tilde{s}_j}{\partial q} < 0$, so the above expression is positive.

If we can show that $\tilde{s}_i\tilde{s}_j\left(\frac{w_i^u - w_j^u}{w_i^s - w_j^s}\right)^2 < 1$, then the result on the relative ranking on increases in dispersion follows . The first part of the expression is smaller than one. Note that $\tilde{s}_i\tilde{s}_j = \frac{s_i(1-s_i)}{u_i(1-u_i)}$. We know from Proposition 2 that $s_i > u_i \Leftrightarrow 1-s_i < 1-u_i$, so u_i is closer to 1/2. For any value x on the unit interval the expression $x(1-x)$ is maximized for $x = 1/2$. Since u is closer to 1/2 than s_i, it must be that $u_i(1-u_i) > s_i(1-s_i)$. ∎

B Estimating shocks driving the real oil price

We follow Kilian (2009) in estimating oil supply, aggregate demand and real oil price-specific shocks in the following VAR:

$$\mathbf{z}_t = \mathbf{c} + \sum_{i=1}^{24}\mathbf{A}_i\mathbf{z}_{t-i} + \mathbf{u}_t$$

where vector $\mathbf{z}$ consists of the monthly time series of the growth rate of global oil production, $\Delta oilprod_t$, the deviations in Kilian's linearly detrended log index of global economic activity, rea_t, and the real price of oil, rpo_t: $\mathbf{z} = [\Delta oilprod_t\ rea_t\ rpo_t]'$.

We assume that the residual disturbances, $\mathbf{u_t}$, can be represented as follows:

$$\mathbf{u_t} = \mathbf{A_0^{-1}}\varepsilon_\mathbf{t}$$

where $\mathbf{A_0}$ is lower triangular consistent with the timing assumptions of Kilian (2009) and $\varepsilon_\mathbf{t}$ is a vector of structural shocks which are serially uncorrelated and independent of each other. These timing assumptions postulate that innovations to global oil production $\varepsilon_t^{oilprod}$ contemporaneously impact all of global oil production, global aggregate demand and the real oil price. Innovations to real economic activity ε_t^{rea} contemporaneously impact global aggregate demand and the real oil price but oil production only with a month's lag. Finally, innovations to the real oil price ε_t^{rpo} have an immediate impact only on the real oil price but affect oil production and aggregate demand only with a month's lag.

The data for global oil production January 1973-November 2015 come form the Energy Information Administration, Table 11.1b World Crude Oil Production.[12]

Data on global economic activity were downloaded from Lutz Kilian's website who has updated and extended this time series until 2015 compared to the version published alongside Kilian (2009).[13]

To measure the real price of oil, we obtain data on refiner acquisition cost for imported crude downloaded from the EIA[14]. Like Kilian (2009) who follows Barsky and Kilian (2002), we use the producer price index for fuels and related products, item crude petroleum, from BLS. We then deflate these nominal data by the U.S. consumer price index for all urban consumers, all items less energy, also downloaded from FRED[15], to obtain a measure of the real price of oil.

C Evidence on the Energy-Skill Complementarity

Our model and the original results by Polgreen and Silos (2009) relied on a complementarity between energy use and skilled labor. Polgreen and Silos (2009) inferred this relationship from the fact that the skill premium is negatively correlated with the real oil price. So before we study the response of wage dispersion, we provide direct establishment-level evidence for this complementarity by comparing wage changes across skill groups in establishments with different energy efficiencies. To do this, we estimate the following regression for the log wage for establishment i at time t

$$\log w_{it} = \beta_0 + \beta_1 t + \beta_2 Oil_t + \gamma X_{it} + \varepsilon_{it} \tag{22}$$

where Oil_t is a measure of the exogenous oil supply shock and X_{it} is a set of control variables at the aggregate and the plant level possibly containing a plant fixed effect.

[12] http://www.eia.gov/beta/MER/index.cfm?tbl=T11.01B#/?f=M&start=200001.
[13] http://www-personal.umich.edu/ lkilian/reaupdate.txt.
[14] http://www.eia.gov/dnav/pet/pet_pri_rac2_dcu_nus_m.htm.
[15] https://research.stlouisfed.org/fred2/series/CPILEGSL.

We differentiate among energy efficient and energy intensive establishments depending on whether fuel intensity in output is above or below the median fuel intensity in the sample. We estimate versions of equation (22) with and without establishment fixed effects (pooled OLS).

Table 10 shows the effects of oil supply shocks on wages and provides micro-level confirmation of this complementarity: after an oil supply shock, skilled wages decline by more than unskilled wages by about a factor of 2.5. The wage decline for both skilled and unskilled wages is stronger in energy intensive establishments where skilled wages fall by about 1% in absolute amounts after a typical oil supply shock. The decline in unskilled wages is less than half a percent and statistically insignificant in the pooled OLS regressions. For energy efficient establishments the just mentioned effects are smaller and not as significant for skilled wages – all of which are consistent with our model presented in the previous section. The differences in the estimated coefficient from including establishment fixed effects are minor. These regressions show the direct effect on wage dispersion from oil supply shocks as wages fall dissimilar amounts across these two groups.

Table 10: Effect of oil supply shocks on establishment wage levels

	Skilled Wage				Unskilled Wage			
	Energy Intensity		Energy Intensity		Energy Intensity		Energy Intensity	
	low	high	low	high	low	high	low	high
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Oil_t	-0.2042^{**}	-0.2250^{***}	-0.2098^{***}	-0.2504^{***}	-0.0883	-0.1054	-0.1048^{***}	-0.1417^{***}
	(0.0979)	(0.0787)	(0.0266)	(0.0162)	(0.0951)	0(.1210)	(0.0128)	(0.0074)
Time trend	0.0045^{***}	0.0019^{***}	0.0041^{***}	0.0019^{***}	0.0022^{***}	-0.0021^{***}	0.0020^{***}	-0.0008^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0006)	(0.0002)	(0.0001)
Fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	$953k$	$981k$	$953k$	$981k$	$1,022k$	$1,036k$	$1,022k$	$1,356k$

Standard errors in parentheses; $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Note: Effect of an exogenous oil supply shock on wage levels by energy use at the establishment level in the ASM. The supply shock is calculated based on the structural model in Kilian (2009). A positive supply shock *increases* the real price of oil everything else equal. Standard errors are clustered at the year-level. Efficient versus inefficient are defined based on whether a particular establishment has above or below the median share of fuel in revenue in the year and industry.