

# The innovation premium to low skill jobs

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# Motivation

- This paper results from an unexpected fact we found in the data.
- At first we started with the view of combining findings of Aghion et al. (2015) that more innovation generates inequality and the findings of Song et al. (2017) that wage inequality is mostly driven by between firms variance.
- We thus looked at whether innovative firms pay higher wages.

# Our contribution

- We document that innovation is one (important) driver of between-firm differences in wages
  - ▶ using matched employer-employee data for the UK we show that workers in R&D firms get a higher wage (conditional on observables).

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- Somewhat surprisingly, this premium is particularly high for workers in **low-skilled occupations**.

# Our contribution

- We document that innovation is one (important) driver of between-firm differences in wages
  - ▶ using matched employer-employee data for the UK we show that workers in R&D firms get a higher wage (conditional on observables).
- Somewhat surprisingly, this premium is particularly high for workers in **low-skilled occupations**.
- We develop a model where innovative firms exhibit higher complementarity between high and low skill workers.
  - ▶ the model captures the idea that low-skilled workers can have a potentially more damaging effect on the firm's value if the firm is more technologically advanced.
  - ▶ show additional empirical support for the model.

# Plan

- 1 Motivation
- 2 Innovation and wage**
- 3 Innovation and wage by skill groups
- 4 Model
- 5 Confronting the model to the data
- 6 Conclusion

# Data

- Data for the UK 2004 - 2014
- Wages
  - ▶ Annual Survey of Hours and Earning (ASHE)
  - ▶ 1% sample of UK based workers (based on National Insurance number)
  - ▶ panel data - we observe the same individual over a long time
  - ▶ information on labour income *including bonuses*
  - ▶ skill level from occupation code
- Research and Development (R&D) expenditure
  - ▶ Business Enterprise Research and Development (BERD)
  - ▶ census of firms with 400+ employees, below that random stratified sample
- Results today for private firms with 400+ employees
  - ▶ sample includes around 150,000 employees, working in 6,300 firms
  - ▶ accounts for around 70% of R&D
  - ▶ we show robustness to other samples

## Pay by skill categories

Occupation	Hourly pay	% incentive pay	% overtime	Annual earnings
<b>Low skill</b>				
Skill cat 1	8.58	2.59	5.66	13,659
Skill cat 2	11.54	2.23	5.45	21,948
<b>Intermediate skill</b>				
Skill cat 3	13.52	5.23	3.61	25,840
Skill cat 4	16.83	5.23	2.19	32,904
<b>High skill</b>				
Skill cat 5	25.45	7.67	1.46	53,978
Skill cat 6	22.25	6.24	1.10	43,542



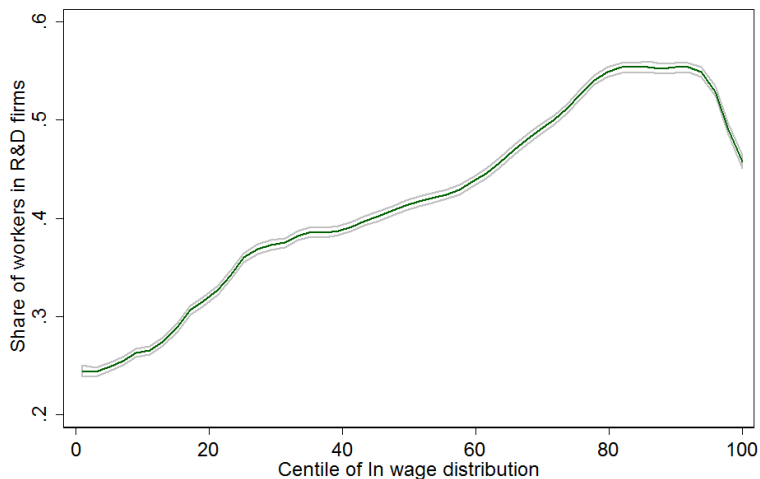
# Measure of innovation intensity

- Expenditures on research
  - ▶ at the **firm** – not enterprise – level
  - ▶ includes both intramural and extramural R&D expenditures
  - ▶ we use R&D intensity, so we divided by employment

$$\ln \text{ RD intensity} = \ln \left( 1 + \frac{RDexp}{Emp} \right)$$

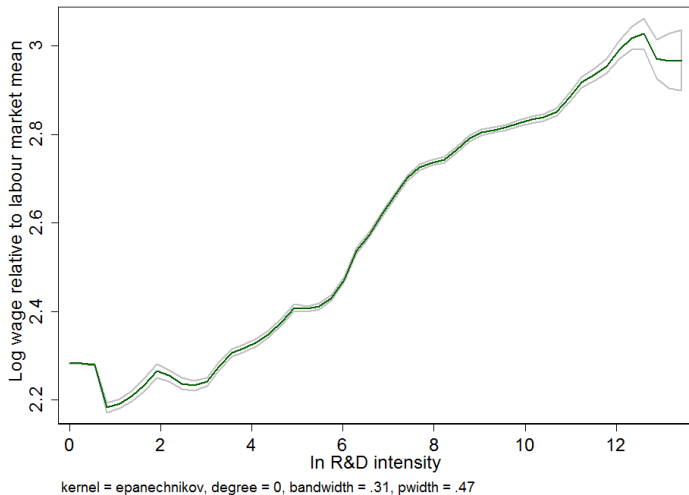
- We also use  $RD = 1$  if a firm ever reports doing R&D
- 1/3 of the firms have  $RD = 1$

## Higher paid workers more likely to work in R&D firm



# Workers in R&D firms are paid higher wages

conditional on labour market mean wage



# The effect of innovation on wages

- A correlation between innovation and wages could reflect many things
  - ▶ innovative firms hire more males workers, more experienced workers and more full-time workers.

	R&D firms	Non-R&D firms
Firm employment	2,828	2,221
Share male (%)	68	57
Share full-time (%)	90	76
Age of worker	40.5	38.1
Tenure of worker	8.9	5.7

- To control for these we estimate

$$\ln(w)_{ijkft} = \beta_1 \ln \text{R\&D intensity}_{ft} + \text{controls} + \epsilon_{ijkft}$$

$i$ : individual  $j$ : occupation  $k$ : labour market  $f$ : firm  $t$ : year

Dependent variable: $\ln(w_{ijkft})$				
	(1)	(2)	(3)	(4)
<b><math>\ln RD_{int_{ft}}</math></b>	<b>0.028***</b> (0.000)	<b>0.016***</b> (0.000)	<b>0.006***</b> (0.000)	<b>0.001***</b> (0.000)
$Age_{it}$	0.059*** (0.001)	0.034*** (0.000)		0.045*** (0.001)
$Age_{it}^2$	-0.001*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
$Tenure_{ift}$	0.023*** (0.000)	0.015*** (0.000)	0.008*** (0.000)	0.016*** (0.000)
$Tenure_{ift}^2$	-0.00028*** (0.00001)	-0.00022*** (0.00001)	-0.00009*** (0.00001)	-0.00019*** (0.00001)
$\ln(emp)_{ft}$	-0.031*** (0.001)	-0.009*** (0.001)	-0.007*** (0.001)	-0.025*** (0.003)
$Male_i$	0.161*** (0.003)	0.146*** (0.002)		0.159*** (0.003)
$Full-time_{ift}$	0.247*** (0.002)	0.071*** (0.002)	-0.001 (0.002)	0.143*** (0.002)
<b>FE</b>	<b>(k,t)</b>	<b>(k,j,t)</b>	<b>i+t</b>	<b>f+t</b>
$R^2$	0.386	0.623	0.888	0.561
N	572,791	572,791	572,791	572,791

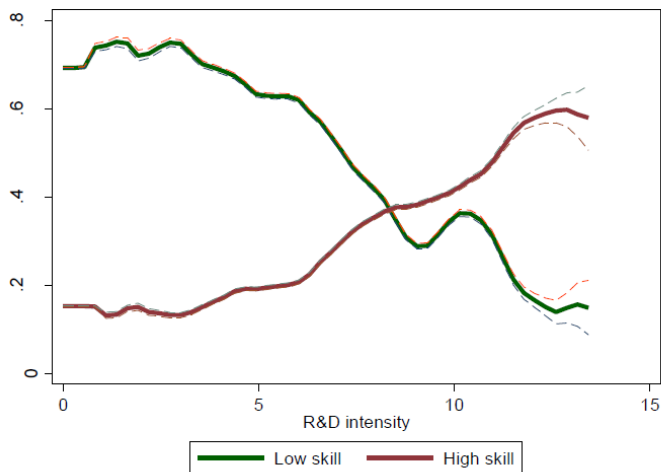
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# Plan

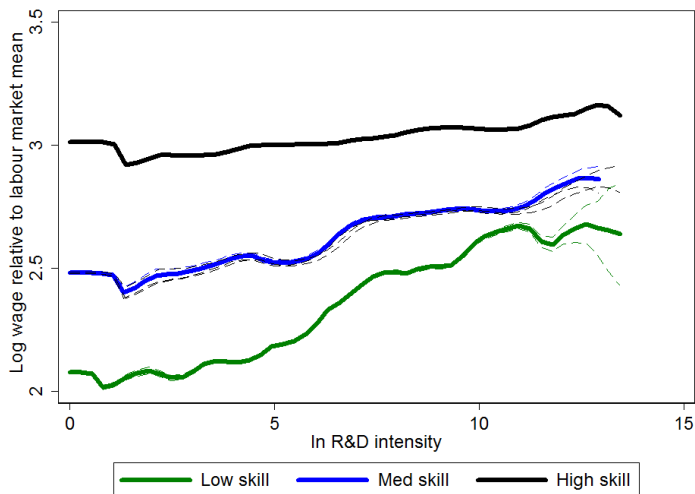
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# Employment, by (occupation) skill and (firm) R&D

R&D firms employ more skilled workers



# The wage premium from working in a high-R&D firm is higher for workers in low-skilled occupations





Occupation	low skill	med skill	high skill	All
$\ln R \& D_{it}$	<b>0.008***</b> (0.000)	<b>0.002***</b> (0.001)	<b>0.000</b> (0.000)	<b>0.002***</b> (0.000)
* <i>lowskill</i> <sub>j</sub>				<b>0.006***</b> (0.000)
* <i>medskill</i> <sub>j</sub>				<b>0.002***</b> (0.000)
$Age_{it}^2$	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
$Tenure_{ift}$	0.009*** (0.000)	0.006*** (0.001)	0.000 (0.000)	0.007*** (0.000)
$Tenure_{ift}^2$	-0.00012*** (0.00001)	-0.00009*** (0.00001)	0.00003** (0.00001)	-0.00009*** (0.00001)
$Firmemp_{ft}$	-0.005*** (0.000)	0.003* (0.002)	0.005*** (0.001)	-0.006*** (0.000)
$Full - time_{ift}$	-0.014*** (0.001)	-0.097*** (0.004)	-0.117*** (0.005)	-0.008*** (0.001)
<b>FE</b>	<b>i+t</b>	<b>i+t</b>	<b>i+t</b>	<b>i+t</b>
N	371,815	95,473	105,482	572,786
R <sup>2</sup>	0.777	0.850	0.885	0.890

# Robustness

## Tables

- These regression results are robust to a number of alternative specifications:
  - 1 Different functional form of R&D
  - 2 Keeping only innovative firms
  - 3 Additive fixed effects ( $i+f+t$ )
  - 4 Removing the financial sector
  - 5 Using different measures of income
  - 6 Other measure of skill
  - 7 Restricting to non moving workers
  - 8 etc.

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# Model intuition

- What explains the stronger effect of innovation on wage for workers in low-skill occupations?
  - ▶ we built a model in which there is complementarity between (some) workers in low and high-skill occupations
  - ▶ the skills of workers in high-skilled occupations are less firm-specific
  - ▶ this provides workers in (complementary) low-skilled occupations bargaining power.

# Model Setup

- 2 workers
  - ▶ high skill with quality  $Q$
  - ▶ low skill with quality  $q$
- Partial O'Ring production function (Kremer, 1993)

$$F(Q, q, \lambda) = \theta [\lambda Qq + (1 - \lambda)(Q + q)]$$

- $\lambda$ : complementarity of the firm's structure
  - ▶  $\lambda = 0$  there is pure substitutability between workers in low and high-skilled occupations and no complementarity
  - ▶  $\lambda = 1$  workers in low and high-skilled occupations are always complementary
- Innovative firms exhibit higher complementarity
  - ▶ (Garicano, 2000; Garicano and Rossi-Hansberg, 2006; Caroli and Van Reenen, 2001; and Bloom et al., 2014)
  - ▶ And evidence below.

# Wage negotiation

- The firm engages in separate wage negotiation with each worker
  - ▶ yields equilibrium wages:  $w^L(q, Q, \lambda)$ ,  $w^H(q, Q, \lambda)$
- If negotiations fail the firm hires a substitute
  - ▶ quality  $q_L$  at wage  $w_L$ , or  $Q_L$  at  $w_H$
  - ▶ we assume  $Q > Q_L > q > q_L > 1$
- We assume  $Q - Q_L < q - q_L$ 
  - ▶ e.g. because of less asymmetry of information
- Wage are then determined by Nash bargaining with outside option for the low and high skill workers  $\bar{w}^L$  and  $\bar{w}^H$ , respectively.

## Effect of an increase in $\lambda$

- One can show

$$\frac{\partial w^L(Q, q, \lambda)}{\partial \lambda} > \frac{\partial w^H(Q, q, \lambda)}{\partial \lambda}$$

Whenever:

$$\frac{\beta^H(1 + \beta^L)}{\beta^L(1 + \beta^H)} < \frac{(q - q_L)(Q - 1)}{(Q - Q_L)(q - 1)}$$

satisfied when  $Q$  is sufficiently large and/or  $Q - Q_L$  is sufficiently small

# Extensions

- Endogenous  $q$  and  $Q$  with training costs
- Endogenous  $\lambda$
- Extend to more than two workers
- Outsourcing



# Empirical assumptions and predictions

- More innovative firms exhibit more complementarity
- Low-skilled workers that remain in a firm benefit more from an increase in  $R\&D$  of the firm than high-skilled workers in that firm
- Low-skilled workers stay longer in more innovative firms (as more time and money is invested in them to getting them from  $q_L$  to  $q^*$ )

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# Complementarity of workers

- We use data collected by the US Department of Labor called the Occupational Information Network (O\*Net)
- These data are collected from workers in the US and aggregated to the **occupation level**
- They provide detailed measures on the characteristics of occupations and the training of workers in those occupations (among other things)
- Aggregate this by skill for different level of R&D intensity
- These are occupation level measures, so any change reflects a change in occupation composition

## Consequences of an error

- The consequences of a worker in a low-skilled occupation making an error are larger in a high-R&D firm than in a low-R&D firm
  - ▶ Mean "consequences of an error"

Consequence of an error

Skill level	Tercile of R&D intensity			
	None (1)	Low (2)	Middle (3)	High (4)
Low	1.00	1.02	1.12	1.14
Intermediate	1.00	1.00	1.02	1.03
High	1.00	1.02	1.00	0.99

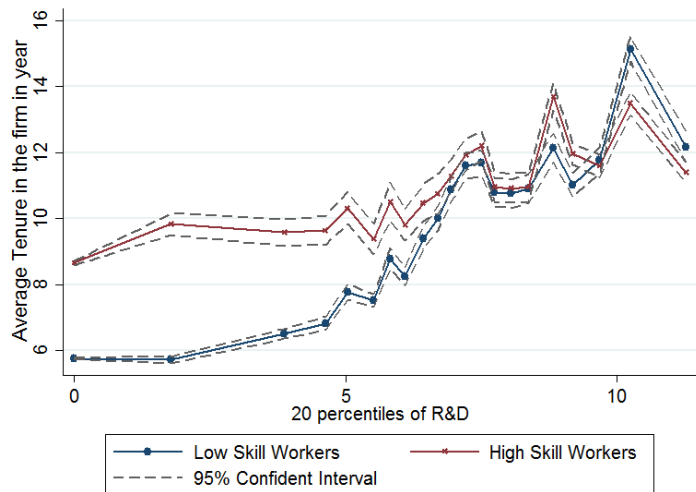
# Training in low-skilled occupations

Back

- The table shows the mean share of workers in low-skilled occupations that receive training (on average in the US, O\*NET data)

	R&D intensity			
	None	lowest tercile	middle tercile	highest tercile
<b>On-site or in-plant</b>				
none	20.3	19.7	18.6	18.5
up to 6 months	65.6	64.3	59.6	54.4
6 months - 1 year	7.7	8.4	10.9	12.9
a year or more	6.4	7.6	10.9	14.3
<b>On-the-job</b>				
none	10.1	10.0	9.3	9.1
up to 6 months	74.8	72.5	66.1	59.9
6 months - 1 year	7.9	9.0	12.5	14.9
a year or more	7.2	8.5	12.1	16.2

# Tenure by skill and R&D



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# Conclusion

- We use new employee-employer matched data that includes information on R&D to show:
  - ▶ workers in innovative firms earn higher wages on average than workers in non-innovative firms
  - ▶ the premium for working in an innovative firm is higher for workers in low-skilled occupations
- We propose a model that is consistent with this finding
  - ▶ some low-skilled occupations are essential for high-R&D firms, these workers are complementary to the high skilled workers, and this allows them to capture a high share of the surplus than equivalent workers in low-R&D firms
- We show empirical support for this model
  - ▶ Low skill workers are more essential for high innovative firms.
  - ▶ tenure of workers in low-skilled occupations is longer in high-R&D firms than in low-R&D firms



# Additional Slides

# Testing different function of R&D

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	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
$\frac{R\&D}{L}$	0.00415***	0.00216***	0.000455***	0.000170*
Hyperbolic with R&D	0.0198***	0.0105***	0.00400***	0.000963***
Hyperbolic with $\frac{R\&D}{L}$	0.0979***	0.0541***	0.0238***	0.00819***
$\ln(1 + R\&D)$	0.0215***	0.0114***	0.00438***	0.00111***
$R\&D > 0$	0.147***	0.0751***	0.0265***	0.00224
$R\&D$	0.282***	0.120***	0.0531***	0.0154**
Fixed Effects	(k,t)	(k,j,t)	i+t	f+t
Observations	572,799	572,799	572,799	572,799

# Robustness to using different measures of income

Back

	(1)	(2)	(3)	(4)
$\ln(R_{ft} + 1)$	0.0286*** (0.002)	0.0275*** (0.002)	0.0360*** (0.002)	0.0553*** (0.003)
Age2	-0.000590*** (0.000)	-0.000559*** (0.000)	-0.000801*** (0.000)	-0.00106*** (0.000)
Tenure	0.00777*** (0.000)	0.00686*** (0.000)	0.00598*** (0.000)	0.0692*** (0.001)
Tenure2	-0.0000870*** (0.000)	-0.0000865*** (0.000)	-0.0000324*** (0.000)	-0.00161*** (0.000)
$\ln(emp)$	-0.00721*** (0.001)	-0.00998*** (0.001)	-0.0152*** (0.001)	-0.0251*** (0.002)
Full Time	-0.000678 (0.002)	0.0132*** (0.002)	0.659*** (0.004)	0.490*** (0.006)
Fixed Effects	i+t	i+t	i+t	i+t
N	572,799	572,586	575,872	570,001
R <sup>2</sup>	0.888	0.907	0.888	0.800

# Removing firms with no R&D expenditures

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	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
$\ln(1 + R_{ft})$	0.0504*** (0.001)	0.0319*** (0.001)	0.00532*** (0.001)	0.00164 (0.001)
Age	0.0650*** (0.001)	0.0407*** (0.001)	0 (.)	0.0560*** (0.001)
Age <sup>2</sup>	-0.000745*** (0.000)	-0.000450*** (0.000)	-0.000546*** (0.000)	-0.000635*** (0.000)
Tenure	0.0139*** (0.001)	0.0108*** (0.001)	0.00528*** (0.001)	0.0122*** (0.001)
Tenure <sup>2</sup>	-0.000198*** (0.000)	-0.000184*** (0.000)	-0.0000765*** (0.000)	-0.000186*** (0.000)
$\ln(emp)$	-0.0137*** (0.002)	-0.0101*** (0.001)	-0.00132 (0.003)	-0.0326*** (0.006)
Male	0.177*** (0.005)	0.161*** (0.005)	0 (.)	0.166*** (0.005)
Full Time	0.200*** (0.006)	0.0318*** (0.005)	-0.0860*** (0.008)	0.137*** (0.006)
Fixed Effects	(k,t)	(k,j,t)	i+t	f+t
N	144,205	144,205	144,205	144,205
R <sup>2</sup>	0.407	0.631	0.917	0.512

# Alternative definition of skill levels

Back

	Dependent variable: $\ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
$\ln(R_{ft} + 1)$	0.0359*** (0.007)	0.0339*** (0.003)	0.00985*** (0.003)	-0.00117 (0.002)
$Age^2$	-0.000208*** (0.000)	-0.000361*** (0.000)	-0.000613*** (0.000)	-0.000875*** (0.000)
Tenure	0.00733*** (0.001)	0.00932*** (0.001)	0.00342*** (0.001)	0.00144** (0.001)
$Tenure^2$	-0.000124*** (0.000)	-0.000151*** (0.000)	-0.0000538*** (0.000)	-0.00000546 (0.000)
$\ln(emp)$	0.00360* (0.002)	-0.00645*** (0.001)	0.000285 (0.003)	0.00625** (0.003)
Full Time	-0.0428*** (0.006)	-0.0159*** (0.003)	-0.120*** (0.011)	-0.118*** (0.013)
Skill Level	1 (low)	2	3	4 (high)
Fixed Effects	i+t	i+t	i+t	i+t
N	92,305	268,760	104,647	107,087
$R^2$	0.701	0.784	0.870	0.900

## Appendix: model

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- In case where  $n \geq 1$  low-occupation workers and  $m \geq 1$  high-occupation workers. We determine equilibrium wages using ex post negotiation Stole and Zwiebel (1996).
- If the  $n^{\text{th}}$  low-occupation worker refuses the wage offer  $w_n^L$ , then the remaining  $n - 1$  low-occupation workers renegotiate a wage  $w_{n-1}^L$ .
- By induction, this provides a generic expression for the two equilibrium wages  $w_{n,m}^L(Q, q, \lambda)$  and  $w_{n,m}^H(Q, q, \lambda)$  (up to a constant in  $q$ ,  $Q$  and  $\lambda$ ):

$$w_{n,m}^L(Q, q, \lambda) = \frac{(q - q_L)\lambda\theta}{n(n+1)} \sum_{i=0}^n iQ^m q^{i-1} - \frac{\theta(1-\lambda)}{2}(q - q_L)$$

$$w_{n,m}^H(Q, q, \lambda) = \frac{(Q - Q_L)\lambda\theta}{m(m+1)} \sum_{i=0}^m iq^n Q^{i-1} - \frac{\theta(1-\lambda)}{2}(Q - Q_L),$$

## Appendix: model

- Assume  $n = 1$  and  $m = 2$

$$\frac{\partial w_{1,2}^L(Q, q, \lambda)}{\partial \lambda} = \frac{\theta(q - q_L)(Q^2 - 1)}{2}$$

and

$$\frac{\partial w_{1,2}^H(Q, q, \lambda)}{\partial \lambda} = \frac{\theta(Q - Q_L) \left( \frac{q(1+2Q)}{3} - 1 \right)}{2},$$

- And since  $Q > q$  implies that:  $q(1+2Q) < Q(1+2Q) < Q(Q+2Q)$  (recall  $Q > 1$ ), we have  $\frac{q(1+2Q)}{3} - 1 < Q^2 - 1$ , which, combined with the assumption that  $(Q - Q_L) < (q - q_L)$ , immediately implies that:

$$\frac{\partial w_{1,2}^L(Q, q, \lambda)}{\partial \lambda} > \frac{\partial w_{1,2}^H(Q, q, \lambda)}{\partial \lambda}.$$