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Skill, Innovation and Wage Inequality: Can Immigrants be the Trump Card?

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Skill, Innovation and Wage Inequality: Can Immigrants be the Trump Card?*

Abstract

With the ensuing immigration reform in the US, the paper shows that targeted skilled immigration into the R&D sector that helps low-skilled labor is conducive for controlling inequality and raising wage. Skilled talent-led innovation could have spillover benefits for the unskilled sector while immigration into the production sector will always reduce wage, aggravating wage inequality. In essence, we infer: (i) if R&D inputs contributes *only* to skilled sector, wage inequality increases in general; (ii) for wage gap to decrease, R&D sector must produce inputs that goes into unskilled manufacturing sector; (iii) even with two types of specific R&D inputs entering into the skilled and unskilled sectors separately, unskilled labor is *not always* benefited by high skilled migrants into R&D-sector. Rather, it depends on the importance of migrants' skill in R&D activities and intensity of inputs. Inclusive immigration policy requires inter-sectoral diffusion of ideas embedded in talented immigrants targeted for innovation. Empirical verification using a VAR regression model in the context of the USA confirms the conjectures, and the empirical results substantiates our policy-guided hypothesis that skilled immigration facilitates innovation with favorable impact on reducing wage-gap.

JEL-Codes: F220, J310, O150.

Keywords: H1B, immigration, innovation, wage gap, skill, R&D, policy, RAISE Act, VAR.

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"How educated immigrants are matters because, although the economic gains for low-skilled migrants of moving to America are great, the benefits to the American economy are not clear. Highly skilled immigrants, by contrast, offer a lot to their adopted country. Education seems to matter much more than where people come from."—pg. 25, *The Economist*, August 12th, 2017 (Attitudes to immigration. Still Yearning. *The Economist*, pp. 25—26. August 12th, 2017.)

**With whatsoever no intention, use of the word 'trump' here is based on Merriam Webster definition where trumping up means 'overriding' or 'winning over' or 'a decisive overriding factor or final resource, or a dependable and exemplary person.' See <https://www.merriam-webster.com/dictionary/trump>.

1. Introduction:

No other issue has received so much attention in recent policy debates as the issue of role of immigrants for economic growth and development of the US economy, and it has raised controversies in different camps, either supporting or opposing it.⁴ Recent presidential debates, since the time of President Barack Obama, have focused on the high-profile H-1B program among other specific policies. Also, European refugee crisis from war-ravaged zones has spawned the conflict for assimilation of migrants with frictions. Current uproar about migration and assimilation of foreigners, frequently heard arguments resonate with the discussion on domestic impact on labor market, especially with respect to wage dispersion between skilled and unskilled workers in the aftermath of influx of immigrants. As both types of labor immigrate into the developed nations with the prospect of better income and socio-economic conditions, the heated debate about repercussions on rich host's domestic economy is replete with controversies. As skilled immigrants contribute to the rich nations by dint of their talents and knowledge (for example, in high tech industry and Silicon Valley)⁵, while unskilled workers displace the native low-skilled one (e.g., high school dropouts or those with non-tertiary education level), the debate essentially hinges on the issue of benefits and costs of curbing skilled vis-à-vis unskilled migrants. Gordon (2016) has offered a detailed study on the U.S economic growth and what is in store for her unless some appropriate measures are taken for nurturing innovation by exploiting ingenuity of workers.

Recent U.S. election thanks to President Trump's policy of curbing immigration has attracted academic interests on role of immigrants—especially skilled talents—in contributing to the U.S. economic growth, and also there are concerns for trade war and global imbalances (Salvatore and Campano 2019, Salvatore 2017, Stiglitz 2018). The introduction of Reforming American Immigration for Strong Employment (RAISE) Act in the US senate in February 2017 (revised in August 2017) aims to reduce over 10 years the legal immigration by 50%, as well as restrictions on green card, cap on

⁴ The most recent is the one announcing the repeal of DACA program on September 5th, 2017.

⁵ Economist article (ibid.). Feldstein (2017) highlights entrepreneurial culture and role of green card for talent mobility.

refugees, and termination of visa diversity lottery. This will affect both skilled and unskilled workers.⁶ Deferred Action for Childhood Arrivals (DACA) is another, which was ended in March 2018. As Kerr (2019a) has mentioned that as immigrants contribute 25% of US patents and entrepreneurship, more than 50% PhD students in STEM are foreign-born, national regulations constraining talent flows would have pronounced effects on sectors confronting new technological advancement, and developing ideas. Inclusive Policy for assimilating global talents is important as it complements innovation policy as well (Kerr 2019b, Stiglitz 2018, Summers 2018).

Not only in the U.S., recent Brexit phenomenon or elections agenda of France for the nationalist party, or for that matter the dissonance or antipathy towards the EU (and hence, moving out of EU) are also pointer to the fact that ‘immigration’ is a major agenda to cure domestic economic malaise in the labor market. But, ironically EU Horizon 2020 or Talent Mobility Program under FP 7 (Seventh Framework Plan) are opening doors of ‘global pool of talents’ via research and brain pool initiative. So does South Korea in a non-English speaking environment to harness global talents to research, innovate and do cutting-edge research to enhance the frontier of technology.

Many economists have raised concern about such anti-immigration (or, anti-globalization) forces and their potentially grave impacts in future. Without assigning malice or being suspicious, can immigration turn into opportunity? This paper throws light in that direction where skilled migration-led innovation can have spillover benefits for the unskilled under certain plausible conditions.

With global connectivity, migration is one dimension of networks for knowledge (Gould and Panterov 2017). Thus, it would affect productivity of innovation-user sectors. Tension between skilled native versus skilled immigrant talents cannot be overlooked. Similarly, as technologies are not confined and rather percolate or diffuse across sectors/firms, the “labor-linking” nature of such aspects can no way be underestimated for welfare of skilled vis-à-vis unskilled (Basu 2017). Otherwise, backlash will follow with adverse consequences unless innovation is conducive (Baily 2014). It is pertinent to

⁶ https://en.wikipedia.org/wiki/RAISE_Act and https://www.aier.org/research/unskilled-immigrants-do-not-harm-americans?utm_source=Web+Articles+08202017+Prospects+&utm_campaign=Web+Articles+08202017+Prospects+&utm_medium=email Basu (2018) calls it “xeno-protectionism”.

study the impacts of skilled immigration on innovation of such developed economies and how does it cause ‘tension’ in the developed destination economies’ internal labor market. Afonso and Holland (2018) discusses the roles of import tariffs on steel and taxes on multinationals for US labor market showing adverse impacts on wages of lower-skilled workers and job losses, due to skill-intensive innovation. However, restricting immigration could be counter-productive via contraction of innovative sector/s producing R&D output used as inputs into manufacturing sectors. Skilled migrant differs in terms of productivity from native skilled, hence, wage differentials exist.

This paper adds value by exploring the role skilled immigrants in innovation in countries like the US, and how does that affect the wage gap. In other words, we analyze under what conditions the adverse wage impact could be arrested so as to make immigration policy inclusive.⁷ As Kerr (2016) has mentioned: “These discussions naturally lead to a key objective that research should address over the next decade, namely, to trace out how high-skilled migration impacts inequality within and across countries. ... Second, to understand the impact of high-skilled migration for inequality, we need to understand the real distribution of returns. This task is again quite complex and requires extensive micro-data work.” Supporting high-skilled immigration to a limited extent, Borjas (August 2017) has argued that: “Exceptional high-skill immigrants will introduce knowledge and abilities that we will learn from, making us more productive, and expanding the frontier of what is economically possible in our country. And high-skill immigration, unlike low-skill immigration, *will reduce*, rather than increase, income inequality.” But unskilled immigration is thought to be harmful.

In order to analyze this complex interplay of factors, repercussion across sectors and labor types, a general equilibrium mixed-specific factor model in trade based on Jones (1965, 1971) is employed. A stylized specific factor model and its variants with three sectors--skilled and unskilled sectors, and an R&D (innovative) sector, and three primary inputs, viz., capital, two skilled labor types, and unskilled worker ---is developed. R&D innovation—produced via specialized talent/skill and capital— is used in both the final goods sectors. Depending on skill and/or, R&D-intensity in the sectors,

⁷ Inclusive growth and development agenda focuses on assimilation of diaspora, not discrimination or curb of global talent flows. As globalization is in full swing, restricting labor migration is impossible thanks to, inter alia, labor-linking technology (Basu, K. 2017).

the direction of wage inequality will evolve. In effect, knowledge embodied in high-skilled talents diffuse to other sectors. For an inclusive immigration policy absorbing unskilled labor in the diaspora, we see that innovation should be having spillover effects across sectors and therefore, as opposed to opposition immigration could turn into opportunity. As will be furnished below, this has ramifications for distributional consequences across the economy.

Section 2 offers background studies which motivates the theoretical model in section 3. Section 4 derives some comparative static results with intuitive discussion on policy implications. Section 5 offers stylized facts, and empirical testing of the core hypothesis, while section 6 concludes based on policy-guided hypothesis testing.

2. A Bird's Eye (Re-)view of Prior Studies

Crafting migration policies across the world is a complex issue, which calls for careful attention. Literatures abound in the contexts of Australia, Canada, UK, as well as Europe (Kslowski 2018, Cerna 2018, Borjas 2014, etc.). We look at the policy challenges from the perspectives of the USA. Recently, in an excellent survey Abramitzky and Boustan (2017) has documented the historical and current flows of immigrants into the US economy and its impact on the labor market and attributed higher immigration to higher rates of trade, innovation, and economic growth. Regarding the impact on employment and wages in the US economy, the study concludes that: there are skill heterogeneities (and hence, earning differences) among immigrants across 'sending countries' vis-à-vis the destination and immigration takes place for taking advantage of high returns to skill in the US; also, most importantly immigrants not having 'net' negative effects on the economy. Furthermore, it surveys the trajectory of researches showing that even within skill categories natives and immigrants are not perfect substitutes in production, patenting rates, and thus immigration increases total factor productivity via task-specialization.⁸ Understanding immigration policy for US labor market, relative socio-economic conditions, and its importance for characteristics of immigrants are crucial for labor market effects (Cobb-Clark, 1998, Salvatore 2018, Stiglitz 2018). Impact of high-skilled immigration on invention and innovation has been studied in the economics literature—see Hunt and Gauthier-Loiselle (2010), Kerr et al.

⁸ In fact, it finds that 'new arrivals created winners and losers in the native population and among the existing immigrant workers' (p. 1312)

(2016a&b), Akcigit et al. (2017a&B), Summers (2019)—to document their positive contribution in the US economy via creation of ideas, knowledge diffusion, and positive externalities. In the context of Thai manufacturing, it has been shown that unlike developed countries with educated migrants enabling R&D, unskilled immigration from neighboring countries like Myanmar or Cambodia is more like ‘labor-saving technology without facilitating R&D investments, innovation and sustainable growth in the long run (Pholphirul and Rukumnuayakit 2016). In the context of Europe 2020, role of immigration background for R&D targets is emphasized (Rogge 2019). According to the World Bank (2016) study, in 2010, 28 million high skilled immigrants resided in OECD registering 130% escalation since 1990. Four countries in the world—Australia, Canada, UK, and US—account for 70% of these 28 million, with US hosting 41% (11.5 million) of OECD by herself. The report identifies that policy for attracting talents and positive spillovers through skill agglomeration and education apart from decline in trade and transport cost account for this sharp rise. In 2013, in USA the share of foreign-born people in total population was 13.1% with total 41 million immigrants in total (Kim and Lim 2017).

Talented Immigrant workers usually occupy employment mainly in Science, Technology, Engineering and Mathematics (STEM) jobs related to R&D, innovative sectors spurring productivity growth and better economic performance. Role of foreign-born worker—talented inventors, workers with diverse skill spectrum from high, to medium, and low—in contributing to economic development of the host recipient nations has spawned debates and spurred researches which documented positive contribution of high-skilled immigrants for invention and innovation (Kerr 2019a).⁹ There are some evidences of displacement of native skills in sciences and mathematics, and small positive externalities in the US following largest influx of Russian scientists and their ideas during post-1992 Soviet collapse (Borjas and Dorn 2012 and 2014). By studying contribution of doctoral students for innovation for 2300 US science and engineering schools for 1973-1988, Stuen et al. (2012) has found that: ‘Both US and international students contribute significantly to the production of knowledge at scientific laboratories, and their contributions are statistically comparable, consistent with an optimizing

⁹ Kerr (2019a) refers to limits on talent migration as ‘America’s national suicide’.

department. Visa restrictions limiting entry of high-quality students are found to be particularly costly for academic innovation.” Kerr and Lincoln (2010) and Kerr et al. (2016) find that H1B immigrants, foreign doctoral students, and college-educated talents increase patent rates, and positively impact on scientific contributions in the academia in the US (and other developed nations). Using a 1940-2000 panel data, Hunt and Gauthier-Loiselle (2010) has shown that ‘a 1 percentage point increase in immigrant college graduates’ population share increases patents per capita by 9—18 percent’ and ‘immigrants patent at double the native rate, due to their disproportionately holding science and engineering degree’; even they provide complementary skills, such as entrepreneurship, to natives to be more inventive (p.31-32, *ibid.*). they also find that talented immigrants account for 24% of patents and hence, diaspora networks facilitate knowledge diffusion across migrants and natives with different skill spectrum. Using publication citations of Web of Science data, Ganguli (2014) has shown that Russian scientists’ publications in post-1992 when Russian scholars emigrated to the US. Freeman (2014) has provided evidence that increase in foreign-born scientists and engineers in US universities and in the labor market is facilitated by globalization of scientific and technological knowledge as it spawned collaborative works via aligning immigration policies with educational attainment.

Although frictions exist, from the established evidences, immigrants facilitate innovation in the US economy and other countries in Europe. Nathan (2014) has discussed the “wider” impacts of high-skilled migrants in the context of U.S, Europe and other countries to offer the empirical evidence supporting such direct-indirect effects throughout the economies via thoroughfares of such R&D-intensive inputs. In case of US, using Federal Censuses and patent records for 1880-1940, Akcigit, Grigsby and Nicholas (2017b) has offered an historical account of role of migrant inventors (especially European) behind the emergence of fundamental technologies influencing not only the US, but other countries as well. As per their study, immigrants had 16% of patents in areas such as chemicals, electricity, and medical, mechanical-to name a few. Akcigit, Grigsby and Nicholas (2017a) reports that the share of immigrants in all inventors is 30%.¹⁰ Kerr and Lincoln (2010) has found that: ruling out displacement

¹⁰ <http://voxeu.org/article/immigrants-and-innovation-us-history>

effects, Higher H1B admissions increase patenting and science and engineering employment by inventors of either Indian and Chinese names.¹¹

According to Kerr (2013), average skilled immigrants with better quality accounts for about one-fourth of workers in innovation and entrepreneurship sectors and help in technology exchanges and business expansion in other countries including their home. Mostly, these occur in the field of Science, Technology, Engineering and Mathematics (STEM) fields and occupations. Thus, apart from direct benefits there are scopes for spillover or indirect transmission of benefits to other sectors using such innovations. Kerr et al (2016) discusses possibilities of such benefits via talented migrants and calls for a framework analyzing such effects. By constructing a measurement of foreign-born expertise based on share of origin country's patents in a given technology class and the number of migrants to US, Akcigit, Grigsby and Nicholas (2017a) found that immigrant inventors contribute not only to their own activities by generating ideas, but also in the other areas with positive externalities or spillovers via augmenting skills and productivity of domestic inventors; typically, they estimate that '1 standard deviation increase in foreign-born expertise is associated with increase in patents that is 40.8% of its standard deviation, similar to 30% increase in innovation (ibid.).' Breschi et al. (2015) discusses the cases of knowledge spillover or diffusion to host as well as homeland via diasporic network and knowledge remittances for countries such as, South Korea, China, Russia and to a lesser extent, for India.

Using TFP as a proxy for innovation, Fassio, Kalantaryan and Venturini (2015) has shown for the period 1994-2007—in the context of UK, France and Germany—that migrants with their 'foreign' human capital are important in all sectors. They show that high-skilled migrants have positive effects on high-tech sectors while, the medium and low-skill contribute for manufacturing. Not only that, inter-sectoral complementarities also foster such innovation transmission. They highlight the necessity of a migration policy 'focusing on the skill-specific needs of the productive system, strongly connected

¹¹ Beladi et al. (2012) discusses the case of impact of outsourcing on the R&D in the home country and shows that the former reduces the latter as outsourcing emerges as a substitute, but it is complementary elements of product development as home country engages in both kind of R&D. In our model, immigrants enter to contribute for innovation and its diffusion across natives as well as, for reverse technology flows to the source wherefrom immigrants come.

with the actual demand of firms (sectors).¹² Using patent citation as a proxy for knowledge in the context of Europe to USA migration, Douglas (2015) has offered evidence that correlation between international migration and trans-border knowledge flows from source/s to host, viz., US. For example, emigration of 41,000 people from UK to the US between 2001—2005 resulted in 1.23% increase forward citations with British inventors in 2006.¹³ Although there are mixed evidences, such as, Canadian evidence showing modest impact on innovations, however, that is attributed to idiosyncrasy of employment policy and information frictions about credentials (Blit, Zhang and Skuterud 2017). Recently for fostering innovation-led development, the Canadian government is encouraging cross-border talent movement. According to Kerr et al. (2016b): “Canada has been very active in targeting skilled migrants who are denied or frustrated by the H-1B visa system in the United States, even taking out ads on billboards in the United States to attract such migrants.”¹⁴ Horton et al (May 2017) has shown that expansion of digitally connected labor markets facilitate flows of talent across the globe by connecting companies and contractors. Not only that, Basso et al (October 2017) has given evidence computerization led technological change and automation has decimated the routine-tasks, task-specialization, increasing the role of analytical task so as to fuel demand for skilled talent migration as well as that of unskilled immigrants for doing manual tasks and services.

Also, there are evidences of firm heterogeneity in demand for different skill (Deming and Kahn 2016). However, most of the innovations are primarily geared towards the skilled sector where it enhances productivity and does not benefit directly the unskilled sector. One important finding is that high-skilled immigration contribution to innovation and entrepreneurship has wider impact on non-routine biased technical change experienced in rich nations. As high-skilled migration changes occupational distribution, it has effects on labor market via changes in wage gap. In particular, Jaimovich and Sui (2017) have shown that such talent migration has in fact contributed to narrowing of wage inequality since 1980s. Akcigit et al. (2017a) finds wage gap between immigrant

¹² Demand-driven migration policy where tertiary educated migrants specific to sectors with more knowledge content as well as non-tertiary educated migrant workers is emphasized.

¹³ Even return or reverse migration entails knowledge flows as well.

¹⁴ Thum (2004) has discussed that instead of ‘direct immigration policy’ for a common labor market altering the composition of government expenditures by controlling goods and services provision can control migration.

inventors and those with comparable native skilled workers and ‘potentially marginalized groups’ thanks to discrimination. As immigrant inventors through foreign-born expertise affect domestic inventions, ‘labor-linking’ aspects of innovations binding both kinds of labor is important.¹⁵ Hence, myopic immigration policy should not pose barriers to unskilled labor and allow skilled migration for inclusive globalization. Quite aptly Kerr (2019a) has emphasized the need for immigration reforms as anti-immigration rhetoric influencing the immigration policy might drag the ‘American dream’ backward due to innovation deficit. The policy needs to be discussed in a broader framework of development in an integrated way so that strategies in the wider context of labor market effects are implemented fruitfully.

As per Kerr (2013, 2016, 2019a) and Nathan (2014), amongst others, there are substantial gaps in understanding the impact of high-skilled migration across sectors, economies and distributional consequences which needs better theorizing alongside empirical evidences. In what follows, we offer a theoretical framework for tracing general equilibrium impacts to show under what conditions such high-skilled talent migration led innovation could improve wage inequality. Competitive trade models could capture such effects (Jones and Marjit 2009, Chaudhuri and Marjit 2017, Chaudhuri and Yabuchi 2011-to quote a few).¹⁶ Ours is different from Cobb-Clark (1998) and Borjas (2014) where migration decisions (self-selecting choice) are modeled incorporating the role of immigration policy selectivity and visa cost, for emigrants’ characteristics, earnings differences across priority workers, etc.

3. Core Model

Consider two final goods sectors without any intersectoral mobility of labor types in the context of host country like the US: Skilled (X) and Unskilled manufacturing (Y).

¹⁵ As opposed to trade, in the endogenous growth literature, skill-biased technological change (SBTC) is a prime suspect for wage inequality. However, recently Parro (2013) has identified the role of skill-biased trade—attributed to fall in trade costs causing decline in capital goods prices—for skill premium via capital-skill complementarity. This is not the subject of our paper. In this paper, ‘place premium’ is more pertinent as driving force underlying inflows of foreign-born workers into rich hosts.

¹⁶ These kinds of models are plenty, such as, Marjit and Kar (2013) showing role of capital flows causing two-sided wage gaps between skill types as some industries disappear due to factor price changes; Beladi et al. (2011, 2013) has considered trade and skill premium in the context of skill formation and finite changes; Mandal and Marjit (2010) has considered the role of engagements in corruption by skill and unskilled workers resulting in wage inequality; Kar and Beladi (2017), on a different note, modeled the case of illegal immigrant trafficking, and smuggling of unskilled workers and impacts on illegal wages of unemployment benefits. All these models demonstrated the elegance of a general equilibrium mechanism to arrest the effects of contemporary real world issues. However, the phenomena of H1B restrictions is as recent a policy shock that its ripple effects could only be analyzed within such an eclectic framework. This is our value-addition.

Another sector (M) produces specialized R&D inputs (i.e., R&D-intensive intermediate input embodying innovation) using specialized skilled labor with research talent (S^*) (i.e., those with acumen for research and innovation potential) and capital (K). Unlike Jones (1971), here M is mobile R&D input used in both X and Y sectors along with heterogeneous immobile specific factors skilled labor (S) and unskilled labor (L). ‘M’ is innovative sectors while X and Y are innovation-user sectors. Thus, two different skill categories (viz., S and L) have access to produced R&D-input (M). In the basic model, S, S^* , L, and K are not mobile intersectorally.¹⁷ We assume perfect competition in product and factor markets. The production setup is generally represented as:

$$\left. \begin{aligned} X &= X(S, M) \\ Y &= Y(L, M) \\ M &= M(S^*, K) \end{aligned} \right) \quad (E1)$$

Production functions in (E1) are assumed to exhibit linear homogeneity and diminishing returns (DMR) to respective inputs. Following notations are used to describe the model:

X: Skilled sector

Y: Unskilled sector

M: R&D sector for specialized inputs catering to X and Y.

P_j : exogenously given prices for j^{th} final good, $\forall j \in \{X, Y\}$ and P_m is price of M

w : Unskilled labor’s wage in the host country

w_s : Skilled labor’s wage in the host. Assume originally, $w_s > w$.¹⁸

w_s^* : Specialized Skilled labor’s wage (or, return to innovation talent).

r : Return to homogeneous capital.¹⁹

$a_i^j = i^{\text{th}}$ input required to produce 1 unit of j^{th} good, $i = L, S, S^*, K, M$; and $j \in \{M, X, Y\}$.

¹⁷ Subsequently, to explore the implications under different scenarios, variant of the basic model will be discussed in the paper. Beladi, Marjit, and Weiher (2011) is an important contribution for analyzing skill demand in the context of emerging economies like India and China. Current paper is in the context of developed US economy and for mobility of high skilled talents from sending to receiving nations.

¹⁸ Even in developing economies skilled labor attracts considerable higher wage than their unskilled counterpart, although levels are *lower than* the rich nations. Income gap is persistent in these nations with incidence of poverty.

¹⁹ K is domestic capital or could be conceived as composite capital made of foreign and domestic types. Given the primary focus of the paper, we *do not distinguish* capital by origin. However, the model could be extended to incorporate foreign capital with higher premium and could study the impact of differences in relative premium between domestic and foreign capital on income gap and output response. In this model, *implicit presumption* is: being naturally capital-abundant, foreign capital inflow is already internalized in the economy via composite K.

$\theta_{lj} = w_l a_l^j / P_j$ is the distributive share of l^{th} labor-types in the production of $j \in \{M, X, Y\}$,
 $\forall l \in \{S, S^*, L\}$;

$\theta_{kj} = r_k a_k^j / P_j$ is the distributive share of owner of capital K for M;

$\theta_{mj} = P_m a_m^j / P_j$ is the distributive share of M for $j \in \{X, Y\}$;

$\lambda_{ij} = \frac{a_i^j Z_j}{f_i} = j^{\text{th}}$ commodity's input share in i^{th} factor's endowment, where Z is generic output and

f is generic endowment; $\sigma_j, \forall j \in \{M, X, Y\}$ is the elasticity of substitution in production.

$\bar{K}, \bar{S}, \bar{L}$, and \bar{S}^* are factor endowments of respective primary inputs.²⁰

“ \wedge ” = proportional changes for a variable, say V, such that generically $\hat{V} = \frac{dV}{V}$.

Note that we have two types of skilled labor—S, for general skill-based sectors, and S* with R&D talents—as specific with $w_s \neq w_s^*$. Supply of ‘M’ requires specialized skill (talent or research skills) and capital (K)²¹. Perfect international capital mobility ensures that with no binding constraints, $r = \bar{r}$. However, S* --specific to ‘M’ sector--is affected by global talent flows or skilled migrants (as well as native talents).

Following (E1), competitive equilibrium with zero pure profit condition implies that:

$$a_s^X w_s + a_m^X P_m = P_X \quad (1)$$

$$a_L^Y w + a_m^Y P_m = P_Y \quad (2)$$

$$a_{S^*}^M w_s^* + a_K^M r = P_m \quad (3)$$

Full employment ensures:

$$a_s^X X = \bar{S} \quad (4)$$

$$a_L^Y Y = \bar{L} \quad (5)$$

$$a_{S^*}^M M = \bar{S}^* \quad (6)$$

$$a_k^M .M = \bar{K}, \text{ with } r = \bar{r}$$

As innovation is occurring in R&D-intensive sectors which is used in X and Y, derived demand for ‘M’ is via increase in final goods production. Better input quality of ‘M’ improves

²⁰ In these countries, “Immigration” is more common due to host economy's better conditions and hence, remittances are source of foreign capital for the source country. As there is no skill shortage, innovation or technical progress is important via knowledge diffusion, diasporic networks, spillovers to native skilled workers, as well as low-skilled labors.

²¹ ‘K’ could be conceived as composite financial capital and/or, capital goods embodying superior blue-print of technology.

quality of X and Y as per the variations in these coefficients.²² The final demand for R&D output is given by:

$$a_m^X \cdot X + a_m^Y \cdot Y = M_d \quad (7)$$

where $a_m^j, \forall j \in \{X, Y\}$ are R&D input-output coefficients.

Given P_m and CRS with DMR, $a_s^X(w_s / P_m), a_L^Y(w / P_m)$, and $a_{S^*}^M(w_s^* / r)$ are the technological coefficients. Thus, *given* P_m and full-employment conditions, using (1) and (2), (4) and (6), we determine X and Y (note with 4 equations, given P_X, P_Y , and P_m we determine X, Y, w_s , and w). Given P_m , as w_s and w are determined factor proportions are also determined. From (1) and (2) as P_m rises, *given* prices of X and Y, wages have to fall. With DMR, as w_s and w fall, a_s^X and a_L^Y have to increase. Via (1) and (2), therefore, *given* P_X and P_Y , a_m^X and a_m^Y have to fall, causing reduction in output of both X and Y, giving $M_d = M_d(P_m), M_d' < 0$. Rise in P_m will cause w_s / P_m and w / P_m to fall.

As $a_s^{X'}(w_s / P_m) < 0$ and $a_L^{Y'}(w / P_m) < 0$, both $a_s^X(w_s / P_m)$ and $a_L^Y(w / P_m)$ increase. Thus, rise in P_m results in use of more of skilled and unskilled labor in respective sectors, and will cause a_m^j to fall across the board triggering fall in final goods production. Given equations (3) and (6), with DMR, and via envelope condition (Jones 1965), we can infer that as P_m rises (given r and a_K^M) w_s^* must go up, $a_{S^*}^M$ falls, supply of M (M_s) increases such that $M_s = M_s(P_m), M_s' > 0$.

$$M_d = M_s \Rightarrow a_m^X \cdot X + a_m^Y \cdot Y = M_s \quad (7')$$

(7') intrinsically corresponds to the full-employment of produced means of production (M). With $M_d = M_s, P_m$ is determined.

As a whole, we have 7 equations (4 full-employment conditions, and 3 price equations for $P=AC=MC$) and given exogenous world prices P_X and P_Y , we determine 7 variables, viz., outputs of X, Y, and M; and input prices w_s, w_s^*, w, P_m .

4. Equations of Change: Analysis of Results

4.1 Basic Model

²² Of course, better engineer, scientists and talents will improve quality of X and Y; however, here we do not model quality ladder or, variety of R&D inputs.

Following discussions in preceding sections, for tracing the effects of talent immigration on innovation, we consider first the case that S^* is affected by talent immigration *targeted for innovative sector* only.²³ We consider comparative statics parametric changes to focus on ensuing policy changes. For enumerating proportional changes for the equation system (1) to (3), employing envelope theorem (Jones 1965), we derive, following Sec 3, the factor-return shares— $\theta_{lj}, \theta_{kj}, \theta_{mj}$ —to obtain:

$$\theta_{SX} \widehat{w}_S + \theta_{mX} \widehat{P}_m = \widehat{P}_X \quad (8)$$

$$\theta_{LY} \widehat{w} + \theta_{mY} \widehat{P}_m = \widehat{P}_Y \quad (9)$$

$$\theta_{S^*m} \widehat{w}_{S^*} + \theta_{Km} \widehat{r} = \widehat{P}_m \quad (10)$$

Proposition 1. *Following high skilled immigration into the innovative R&D-sector, the wage inequality will improve iff $\theta_{mY} > \theta_{mX}$.*

Proof: Given $r = \bar{r} \Rightarrow \widehat{r} = 0$, and from (10) $\theta_{S^*m} \widehat{w}_{S^*} = \widehat{P}_m \cdot \widehat{P}_X = \widehat{P}_Y = 0, \widehat{P}_m \neq 0$. With immigration targeted to M-sector ($\Delta S^* > 0$), w_{S^*} falls, and P_m falls too. Via (8) and (9), both $\widehat{w}_S > 0, \widehat{w} > 0$. Using (8), (9) and (10), given shares and wage changes

$$\widehat{w}_{S^*} = -\frac{\theta_{SX}}{\theta_{S^*M} \theta_{MX}} \widehat{w}_S = -\frac{\theta_{LY}}{\theta_{S^*M} \theta_{MY}} \widehat{w} \Rightarrow \widehat{w}_{S^*} < 0.$$

X and Y production rise causing increase in demand for ‘M’ concomitant with its supply to match. $\widehat{P}_X = \widehat{P}_Y = 0, \widehat{P}_m \neq 0$. Using (8) and (9),

$$\widehat{w}_S = -\frac{\theta_{mX}}{\theta_{SX}} \widehat{P}_m \text{ and } \widehat{w} = -\frac{\theta_{mY}}{\theta_{LY}} \widehat{P}_m \Rightarrow \frac{\widehat{w}_S}{\widehat{w}} = \frac{\theta_{mX} \theta_{LY}}{\theta_{SX} \theta_{mY}}. \text{ Thus, using}$$

$\theta_{LY} = 1 - \theta_{mY}$ and $\theta_{SX} = 1 - \theta_{mX}$ we show that $\frac{\widehat{w}_S}{\widehat{w}} > 1$ iff $\theta_{mX} > \theta_{mY}$. (QED.) As P_m falls,

w_S and w both increase but degree of wage inequality will increase (i.e., $\widehat{w}_S > \widehat{w}$) if

skilled sector is more R&D-input intensive, or if share of unskilled labor in the production cost of Y is higher than the share of skilled labor in X’s cost (i.e.,

$\theta_{mX} > \theta_{mY} \Leftrightarrow \theta_{LY} > \theta_{SX}$). In other words, for inequality to improve (i.e., $\widehat{w}_S < \widehat{w}$)

innovative sector should be contributing more for the unskilled sector (i.e.,

²³ Donald Trump’s recent policy announcement favors post-graduate migrants for granting H1B visas (more to follow on this in Section 4.3).

$\theta_{mY} > \theta_{mX} \Leftrightarrow \theta_{LY} < \theta_{SX}$). Thus, a restriction on migration could have pernicious effect on existing inequality. The intuition is clear: *ex post* with increase in supply of R&D inputs, if R&D's share is more to aid unskilled sector's production, low-skilled worker becomes more productive, registering in higher wage (w) to reduce the prevalent wage gap.

$$\text{From (7) and (7'), we get: } \lambda_{mX} \hat{X} + \lambda_{mY} \hat{Y} = \hat{M}_S \quad (11)$$

where λ_{mij} is the share of the economy's R&D supply used in the production of

$j \in \{X, Y\}$. Let $M_X + M_Y = M$ where $a_m^X \cdot X = M_X$ and $a_m^Y \cdot Y = M_Y$.

Following (4), (5), and (6), we derive:

$$\hat{X} = \hat{S} - \hat{a}_S^X, \hat{Y} = \hat{L} - \hat{a}_L^Y, \text{ and } M = \hat{S}^* - \hat{a}_{S^*}^M \quad (12)$$

Now, *ex post* skilled immigration we infer that $\hat{S}^* > 0$. However, embodied talent or skill-biased technical change (SBTC) latent in the high skilled migrants implies:

$$\hat{a}_{S^*}^M < 0 \Rightarrow \hat{a}_{S^*}^M = -\alpha, \alpha > 0. \quad (13)$$

Thus, using (12) and (13), we get $\hat{M} = \hat{S}^* + \alpha$ (14)

It signifies that talent immigration with knowledge embodiment augments supply of R&D innovations via SBTC. Via (7) and/or, (7') and (14), then we argue that

$\hat{S}^* > 0$ and $\alpha > 0 \Rightarrow \hat{M}_S > 0, \hat{M}_X > 0, \hat{M}_Y > 0$ and given a_m^X and $a_m^Y, \hat{X} > 0, \hat{Y} > 0$.

Suppose, there is rise in immigration directed to X sector (or, increase in native high skilled pool of talents) so that $\hat{S} > 0$, and following earlier presumption about skill-embodiment or skill-upgrading, $\hat{a}_S^X = -\beta, \beta > 0$.

$$\text{Then, analogously } \hat{X} = \hat{S} + \beta \Rightarrow \hat{X} > 0. \quad (15)$$

Considering the 'relative effect' of both types of immigration (i.e., $\hat{S}^* > 0$ vis-a-vis $\hat{S} > 0$), we observe that effective talent of high skilled migrant adjusted for quality (via 14 and 15) augments output in R&D as well as skilled sector while innovation sector contributes

to both skilled as well as unskilled labor. From (14) and (15), $\hat{X} > \hat{M}$ iff

$\hat{S} + \beta > \hat{S}^* + \alpha \Rightarrow (\hat{S} - \hat{S}^*) > (\alpha - \beta)$. With $\beta = \alpha$, it all depends on $(\hat{S} - \hat{S}^*)$. Thus,

differentials between growth in skilled migrants going to X vis-à-vis that in M should be exceeding the differences in rate of technical changes in these sectors. This implies that in order to have higher output in skilled sector, it requires inflows of more foreign-born

expertise, with skill-migrant biased technical change for the hi-tech R&D sector being higher than that in the skilled manufacturing sector. In case of unskilled sector, assuming low skilled migration *without* any superior technical skill upgrading ($\hat{a}_L^Y = 0, \hat{L} > 0$), we see that for output of Y-sector, it all depends on relative magnitude of $\hat{S}^* + \alpha$ and \hat{L} .

4.2 General setting

From the previous case, we see that sectoral R&D-intensity matters for direction of movement of wage gap. However, it is quite plausible that unskilled and skilled sector might not use the same generic R&D (i.e., M). In other words, in a fairly realistic setting *general framework* would be to consider that two different R&D varieties—say, M_1 and M_2 produced with S^* and K as in Heckscher-Ohlin setup—are used in X and Y sectors respectively (i.e., $X = X(S, M_1), Y = Y(L, M_2)$). Also, it is pertinent to assume that the nature of the R&D sector depends on the differences in factor intensities of S^* and K in M_1 and M_2 production. How inequality is affected in this set up and when targeting immigration to X as well as M-sectors? We will see that nature of R&D sector and share of R&D inputs in respective sectors matter. Consider the additional competitive equilibrium with zero pure-profit conditions now: -

$$a_{m1}^X \cdot P_{m1} + a_S^X \cdot w_S = P_X \quad (16)$$

$$a_{m2}^Y \cdot P_{m2} + a_L^Y \cdot w = P_Y \quad (17)$$

$$a_K^{M1} \cdot r + a_{S^*}^{M1} \cdot w_{S^*} = P_{m1} \quad (18)$$

$$a_K^{M2} \cdot r + a_{S^*}^{M2} \cdot w_{S^*} = P_{m2} \quad (19)$$

As before, demand curves for M-types are negatively sloping and equating with respective supplies, prices of each M-varieties are determined. Using envelope condition (Jones 1965), we get: -

$$\theta_{m1X} \cdot \hat{P}_{m1} + \theta_{SX} \cdot \hat{w}_S = \hat{P}_X \quad (20)$$

$$\theta_{m2Y} \cdot \hat{P}_{m2} + \theta_{LY} \cdot \hat{w} = \hat{P}_Y \quad (21)$$

$$\theta_{S^*m1} \cdot \hat{w}_{S^*} + \theta_{Km1} \cdot \hat{r} = \hat{P}_{m1} \quad (22)$$

$$\theta_{S^*m2} \cdot \hat{w}_{S^*} + \theta_{Km2} \cdot \hat{r} = \hat{P}_{m2} \quad (23)$$

From (22) and (23), with $\hat{r} = 0 \Rightarrow$

$$\theta_{S^*m1} \cdot \hat{w}_{S^*} = \hat{P}_{m1} \quad (24)$$

$$\theta_{S^*m2} \cdot \hat{w}_{S^*} = \hat{P}_{m2} \quad (25)$$

Proposition 2. *In a fairly general setting with two different R&D-inputs, with immigration of skilled labor targeted to the R&D input used in the skilled sector, wage inequality will aggravate iff that R&D sector is relatively more immigrants' skill intensive; otherwise, the wage inequality will improve iff it is relatively capital intensive.*

Proof. With exogenous prices, $\hat{P}_X = \hat{P}_Y = 0$. As immigration is targeted to M_1 and M_2 sectors, w_{S^*} has to fall ($\hat{w}_{S^*} < 0$) so that (via equations 24 and 25), $\hat{P}_{m1} < 0, \hat{P}_{m2} < 0$. From equations (20) and (21), therefore, $\hat{w}_s > 0, \hat{w} > 0$. By manipulating (20), (21), (24) and (25), we get as below:

$$\begin{aligned} \hat{w}_s &= -\frac{\theta_{m1X}}{\theta_{SX}} \cdot \hat{P}_{m1} = \frac{\theta_{m1X}}{\theta_{SX}} \cdot \theta_{S^*m1} \hat{w}_{S^*} \text{ and } \hat{w} = -\frac{\theta_{m2Y}}{\theta_{LY}} \cdot \hat{P}_{m2} = \frac{\theta_{m2Y}}{\theta_{LY}} \cdot \theta_{S^*m2} \hat{w}_{S^*} \Rightarrow \\ \frac{\hat{w}_s}{\hat{w}} &= \frac{\theta_{S^*m1}}{\theta_{S^*m2}} \cdot \frac{\theta_{m1X} \theta_{LY}}{\theta_{SX} \theta_{m2Y}} \end{aligned} \quad (27)$$

Hence, given the shares of respective inputs in X and Y, viz., $\theta_{m1X}, \theta_{SX}, \theta_{m2Y}, \theta_{LY}$,

$\frac{\hat{w}_s}{\hat{w}} > 1$ iff $\theta_{S^*m1} > \theta_{S^*m2}$ (or, equivalently, $\theta_{Km1} < \theta_{Km2}$), resulting in worsening of wage inequality. When M_1 is S^* intensive (relatively) than M_2 and M_2 is relatively K-intensive, with skilled migration, M_1 expands more than M_2 because S^* needs more K to work with, which is released from M_2 , causing contraction of its output. X production expands. Consequently, production of Y falls as M_2 does not expand, making unskilled labor (L) surplus so that her wage (w) does not increase as compared to that of w_s .

Conversely, $\hat{w}_s < \hat{w}$ iff $\theta_{S^*m1} < \theta_{S^*m2} \Leftrightarrow \theta_{Km1} > \theta_{Km2}$, resulting in improvement in wage inequality. In this case, as M_1 is relatively K-intensive, increase in high skilled migration does not increase its production much; instead, M_2 —more skilled migrants intensive—inflates, causing expansion of output of Y-sector using unskilled labor (L) and M_2 ; hence, registering relatively more pronounced increase in her wage by fueling demand for L, so that $\hat{w}_s < \hat{w}$.

In another general setting where M_2 used in unskilled sector (Y) is low-quality R&D-input produced with L and K (i.e., not using S^*), here *targeted* high skilled migration (S^*) will cause expansion of output of X via increase in M_1 production, causing $\hat{w}_s > 0, \hat{w}_{S^*} < 0$. With rise in production of X and M_1 , more Capital will flow out of M_2 to M_1 , aggravating wage inequality, that is, $\hat{w}_s > 0, \hat{w} < 0$.

In essence, we can infer: (i) if R&D inputs contributes *only* to skilled sector, wage inequality increases in general; (ii) for wage gap to decrease, R&D sector must produce inputs that goes into unskilled manufacturing sector (*helping the low-skilled*); (iii) even with two types of specific R&D inputs entering into the skilled and unskilled sectors separately, unskilled labor is *not always* benefited by talented or high skilled migrants entering into R&D-sector. Hence, it depends on importance of migrants' skill in R&D activities and intensity of inputs used.

Thus, how critical is the R&D inputs for the skilled and unskilled manufacturing sectors and nature of each of the R&D-sector (i.e., importance of skilled labor vis-à-vis capital for the R&D innovation) are crucial in driving the direction of movement of wage inequality. Facilitated by talent flows, wage gap could go either way, contingent on the contribution of R&D inputs (share in production)—produced by dint of high skilled labors' innovativeness and capital—entering the production of unskilled sector. Thus, nurturing high skilled talents from abroad could make immigration '*inclusive*' via provisioning of innovative input (better technology or knowledge inputs) into other sectors. This could improve productivity of the workers lacking access to technology absorption.

Given this backdrop of analysis, it's pertinent to explore the aspects of targeting skilled immigration—either into skilled manufacturing sector or, innovation or, both—for turning immigration policy— into best opportunity for the diaspora network as well as for the native workers in host country.

4.3 Immigration Targeting, Wage impact and H1B Visa Case:

We consider how wage inequality is affected in the following cases as below:

- (a) *Two different* skill types (S and S*) going into X and M sectors, so that they are specific factors in each sectors
- (b) *Same skill types* contribute equally to both X and M sectors and targeting immigration into X-sector (skilled production) only.
- (c) *Same skill types* contribute equally to both X and M sectors and targeting immigration into R&D (M-sector) only.

Considering (a), it is very much identical as dealt in Sections 4.1 and 4.2.

In case of (b), unlike previous analysis, we now have:

$$S_M + S_X = S \quad (28)$$

$$\Rightarrow a_S^M M + a_S^X X = S \quad (28a)$$

$$a_S^M \cdot w_s + a_K^M \cdot r = P_m \quad (29)$$

The last one generates supply function for M, so that, as before, $M_s = M_d$ gives P_m .

However, here $M_d = a_m^X \cdot X + a_m^Y \cdot Y$ and equation (28a) implies that M_s, M_d now depend on S_M, S_X .

Proposition 3: *Skilled migration targeted into skilled manufacturing will have spillover effect on unskilled wage, both wages will fall, and inequality can go either way.*

Proof. Consider the following equations, by employing envelope condition for (29)

$$\theta_{Sm} \hat{w}_s + \theta_{Km} \hat{r} = \hat{P}_m \quad (30)$$

and the equations (8) and (9) as before (used in Proposition 1). From (8) and (9), Using them, $\hat{w}_s < 0, \hat{w} > 0$, and further,

$$\frac{\hat{w}_s}{\hat{w}} = \frac{\theta_{mX} \theta_{LY}}{\theta_{SX} \theta_{mY}} \quad (31)$$

Thus, using $\theta_{LY} = 1 - \theta_{mY}$ and $\theta_{SX} = 1 - \theta_{mX}$ from (31), we derive, as before, that:

$$\frac{\hat{w}_s}{\hat{w}} > 1 \text{ iff } \theta_{mX} > \theta_{mY} \text{ and the opposite is true (QED.)}$$

With increase in skill migration targeted towards X-sector, demand for M will go up as migrants need more R&D-inputs to work with; however, this triggers rise in P_m, S_M , and M_s , and fall in S_X . Substitution effect, induced by rise in P_m , will lead to rise in a_S^X , decline in X, while S_X goes down, resulting in fall in w_s and w . If Y is more M-intensive ($\theta_{mY} > \theta_{mX}$), 'w' will fall by more; or the other way round. Here, 'w' does not fall as much as 'w_s' declines because the targeted immigration to skilled manufacturing sector yields more derived demand and hence production of R&D, used more intensively without reducing demand for unskilled worker, and therefore, improving productivity. Thus, as before, thanks to the high-skilled migrants, spillover benefits to unskilled sector results in improvement in wage inequality.

As mentioned in case (c), if talent migrants are targeted to R&D-sector only, different mechanism comes into play because now wage impact will move in opposite

direction (i.e., rise) as there will be two reinforcing channels—via both skilled and innovative sectors along with unskilled usage of innovative inputs—working on wages.

Proposition 4: *Skilled migration targeted into R&D-sector will have spillover effect on unskilled wage, and both wages will rise and inequality can go either way.*

Proof. Consider same sets of equations as in cases of Proofs for 2nd and 3rd propositions. However, here talent flows into innovative sector will cause its price to fall (P_m falls) as M_s rises causing downward pressure on its price. S_M rises. As X and Y both use it for their production along with Skilled and Unskilled labor, both wages rise, i.e., $\hat{w}_s > 0, \hat{w} > 0$. However, *iff* X uses M more in its production than Y (i.e., $\theta_{SX} > \theta_{SM}$ and $\theta_{mX} > \theta_{mY}$), and as more L is required in the Y-sector with ‘M’, wage inequality worsens, $\hat{w}_s > \hat{w} > 0$. On the contrary, wage inequality improves ($\hat{w}_s < \hat{w}$), *iff* $\theta_{mY} > \theta_{mX}$. This supports our conjecture that even if same skill types could contribute to skilled manufacturing and/or, innovative R&D sectors, targeting immigration to the latter helps through induced spillover to the unskilled sector using the innovative input relatively intensively in its production. Furthermore, this helps improving wage inequality via reduction of existing wage gap.

All the foregoing analytical exercises in the basic model and its variants or extensions are capable of handling the recently passed bill in the US congress for H1B and L1 visa holders with skill and specialty talents, under which US Citizenship and Immigrations Service (USCIS) issues 65,000 H1B visas and 20,000 for those with advanced degrees in STEM subjects are granted visa annually (H-1B visas to several categories like those in academic and research institutes is exempted from the Congressional mandated limit).²⁴

As mentioned before, under the Trump administration to protect jobs for low-skilled and unskilled American jobs and to avert the ‘sharp decline in wages’ for Americans recently passed legislation Cotton-Perdue bill (RAISE Act) aims to restrict legal immigration by 50% so as to fix immigration at ‘historically normal level’. At the

²⁴ <https://economictimes.indiatimes.com/nri/visa-and-immigration/us-resumes-premium-processing-of-all-h-1b-visa-categories/articleshow/60935385.cms>

same time, the emphasis is on higher wages for the workers.²⁵ Under the ‘Protect and Grow American Jobs Act (HR 170)’, replacement of American workers with skilled H1B employees are prohibited. This will impact the IT professionals’ migration from India. However, the Act ‘dramatically increases the salary requirements for H1B workers’, with an inflation-adjusted minimum salary of US\$ 90,000 raised from 60,000 and the maximum of US\$130,000.²⁶ As per news report quoting Pew Research Center, ‘for eight of the top 10 India-centric IT companies, the average salary for workers on H-1B visas was higher than the median salary for US citizens in computer and mathematical jobs.’²⁷ There are disagreements and rooms for conflicts of interests about the legislation as many doubts it is driven by myths. Not only that, there are shortage of skilled talents in the US for such employment and 20 million job losses every year are not linked to H1Bs, rather it’s a different issue. Except a study by Borjas (2017), most studies find the argument flawed.²⁸

Given the above legislation, *our basic model*—with minor modifications as per the case—is capable of offering cogent insights from a general equilibrium perspective. We consider the cases of no-restriction on H1B visa in both innovation and skilled production sectors, and policy reversals in the current US administration. Consider the following scenarios: -

a) *Case of R&D-sector*: in this scenario, without visa restrictions R&D

talents/professionals come at a cheaper price, so that w_{s^*} falls to internationally low level (or, say at the lower level as that in emerging economies like India or China).

With $r = \bar{r}$, and lower wage level, we determine $\theta_{s^*m} \widehat{w}_{s^*} = \widehat{P}_m$ i.e., it translates into lower price of R&D input (P_m) with flat M_d . Supply of M increases. Both skilled and unskilled production sector expands with capital and labor moving freely. As discussed before, both w_s, w rises as they expand their production with more innovative inputs along with labor types. Low initial P_m implies (from basic model

²⁵ <http://www.hindustantimes.com/india-news/bill-to-halve-the-number-of-legal-immigrants-can-hit-indians-working-in-the-us/story-W6pi6DjtMy1ZlqWHEan1bP.html>

²⁶ <https://economictimes.indiatimes.com/nri/visa-and-immigration/congressional-committee-votes-to-increase-minimum-salary-of-h1b-visa/articleshow/61665673.cms>

²⁷ <https://economictimes.indiatimes.com/nri/visa-and-immigration/congressional-committee-votes-to-increase-minimum-salary-of-h1b-visa/articleshow/61665673.cms>

²⁸ <https://www.politico.com/magazine/story/2017/08/04/why-trumps-new-immigration-bill-makes-sense-215457>

equations) that w_s was high while w_{s^*} was low. Therefore, we see possibilities of *inter-skill* groups as well as *intra-skill* groups movement of inequality. *With policy reversals*, where restrictions are in place with high salary going to the cream of H1Bs, now w_{s^*} will rise reflecting on higher P_m , and raising demand for innovation sector output. Then, from the basic model we can see innovative sector contracts along with both skilled and unskilled production sectors resulting in $\hat{w}_s < 0, \hat{w} < 0$. Following propositions 1 and 4 above, wage inequality can go either way depending on the relative input-intensity (i.e., intermediate R&D input vis-à-vis skill labor types).

b) *Case of Skilled Production Sector*: in this scenario, without visa restrictions H1B workers come at a lower international price level (as from India, Korea or China) to be absorbed into the skilled production sector (X in the basic model). This implies adjustment of w_s to a lower level, and as before, P_m is determined with flat demand curve for M-sector. Supply of M determines its actual use. However, with low wage in production sector demand for R&D input goes up via X-sector and P_m inflates causing $\hat{w}_{s^*} > 0$. Substitution effect (and DMR) will lead to fall in a_m^X, a_m^Y and rise in a_s^X, a_s^Y , and $\hat{X} < 0, \hat{Y} < 0$. Increase in supply of innovative input and fall in its demand will lead to exports of R&D-input (kind of reverse outsourcing R&D) at the world price of P_m . This makes it exogenous like w_s . Inequality between two kinds of labor—R&D professionals and skilled production workers—will rise; however, as we saw before, between skilled and unskilled it can go either way depending on use of innovative input intensity in use. With policy reversal, restrictions on H1B and higher wage, w_s will increase and so will w . Also, P_m falls, export of M contracts, and hence w_{s^*} is reduced.

Thus, both the cases illustrate that whether it's win-win depends on H1B policy effectiveness in respective skill-specific sectors. In fact, Khanna and Morales (July 2017) has discussed in a general equilibrium simulation model doing counterfactual analysis in the context of India that the IT exuberance and US immigration policy are mutually conducive; in other words, they showed that high-skilled immigration is mutually beneficial for both the countries as it enabled India to move up the occupation ladder while for US, the benefits occurred via innovation and spillover to natives. Koppel and

Plunnecke (2017) has shown that in the context of even Germany and Europe qualified immigrants with skill have played major role in STEM employment, esp. from India rising to the top (in Germany, for example, Indian STEM employment has doubled pushing China in third rank), thanks to the diasporic network effects as well as skill.

5. Empirical Validity and Hypothesis Testing:

5.1 Variables and Data Sources

The present section of the paper uses aggregate industry level data for USA to examine the relation between the skilled-to-unskilled wage gap for the native workers in the US manufacturing, and the difference in R&D intensity per worker in manufacturing vis-a-vis the R&D (invention/innovation) sector. R&D has a positive effect on innovation and human capital-induced skill is necessary for innovation and absorption (OECD 2011, Das 2015, Pegkas et al. 2019). Our primary aim is to observe the impact of skilled immigration in USA on the skilled-unskilled native wage inequality. Since skilled immigration in the country gets predominantly absorbed in the non-farm manufacturing companies identified by codes 31, 32, 33 of the North American Industry Classification System (NAICS), and the innovative companies identified by NAICS Code 54, we have used the data for number of H1B visa approvals in the manufacturing sectors (NAICS Code 31, 32 and 33) in a particular year as a proxy for skilled immigrants (S_{L1}) joining that sector.²⁹ Similarly, number of H1B visa approvals in the innovative sectors (NAICS Code 54) for a particular year is the proxy for skilled immigrants (S_{L2}) joining that sector in the given year. The data for H1B visa approvals for the entire period of study is obtained from the database of US Citizenship and Immigration Services (USCIS) published and maintained by the US Department of Homeland Security. We hypothesize that a greater inflow of immigrants in the innovative sector reduces skilled-to-unskilled wage inequality among native workers in the United States.

The education level of the US native workers is used as a proxy for skill distribution, and the wage data for different skill (education) levels is obtained from the database of the Bureau of Labour Statistics (BLS) published by the US Department of Labour in the form of annual averages of Median Usual Weekly Earnings of full-time

²⁹ Jorgenson, Ho, and Samuels (2019) also use the similar industry classification for Data.

native-born workers. The weighted average³⁰ of the wages of the workers with two lower categories of educational attainment levels (viz. workers with less than a high school diploma and high school graduates with no college degree) is taken as average unskilled wage (w_u) for a particular year. Weighted average of the two higher categories of educational attainment levels (namely, workers with some college degree, and higher than that) represents the average skilled wage (w_s) for a particular year.

The R&D intensity per worker in manufacturing sector for all scheduled years (RDI_1) is obtained by dividing the value of domestic R&D spending by manufacturing companies (in Million \$US) by the value of domestic employment in these companies. Similarly, the R&D intensity per worker in the innovative sector (RDI_2) is the ratio of R&D expenses divided by the value of employment in such companies. Both kinds of R&D data are obtained from the Business R&D and Innovation Survey (BRDIS) of the U.S. Census Bureau and the National Science Foundation/National Centre for Science and Engineering Statistics, for different years. It is noteworthy here that USCIS database covers 2002 to 2017 only and therefore, we have to confine our analysis to a limited period of 16 years. The short duration of this low-frequency data further hinders application of standard time-series techniques for the main variables chosen to capture the theoretical prediction of the previous section. Nevertheless, we later adopt a Vector Autoregressive (VAR) analysis to obtain plausible relations between immigrant flows to the sectors identified and the native skilled-to-unskilled wage inequality.

5.2 Graphical Analysis

We first attempt to predict the trend of our primary variables. Having w_s , w_u , RDI_1 and RDI_2 values for different years, $\ln w_g$ (log of skilled-unskilled wage gap in absolute terms) is calculated as $\ln(w_s - w_u)$ and RDI_g (gap in R&D intensity per worker) is calculated as $[(RDI_2 - RDI_1)]$, since $RDI_2 > RDI_1$ generally]. These are plotted as long-run predictions with 95% confidence intervals associated with each one of these.

³⁰ The number of native employed laborer with a particular level of educational attainment is taken as weight for that category.

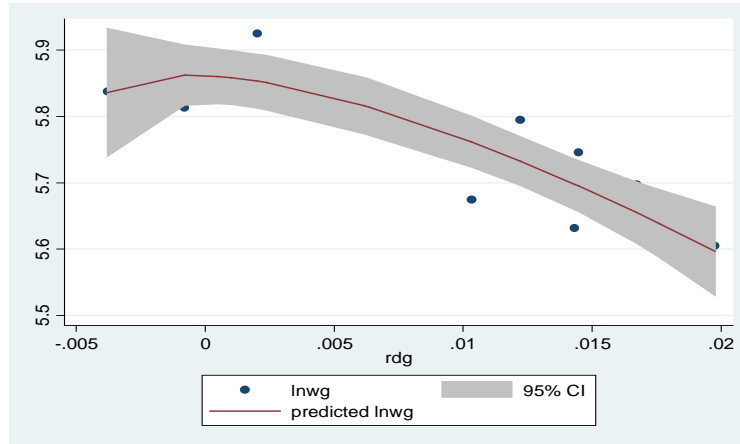


Figure 1: *Predicted Skilled-Unskilled Wage Gap (vertical axis) w.r.t Gap in R&D Intensity per Worker*

Figure 1 depicts the relation between w_g and RDI_g . It shows that as RDI_g rises initially (R&D intensity is higher in manufacturing than innovative sector between -0.005 and 0), w_g rises too, but once it reaches 0 , starts falling secularly thereafter. In other words, for a rise in $RDI_g > 0$ the native wage gap falls unambiguously. This is indicative of the possibility that skilled immigrants joining direct R&D activities lead to improvement in the native wage inequality. Instead, if one looks at the skilled immigration in manufacturing sector (S_{L1}) alone, the native skilled-to-unskilled wage gap clearly rises over a substantial range of inflows (figure 2). Conversely, if the skilled migrants join the R&D sector in the host country, the native wage inequality falls up to an inflow of 100,000 migrants, beyond which the inequality rises steadily.

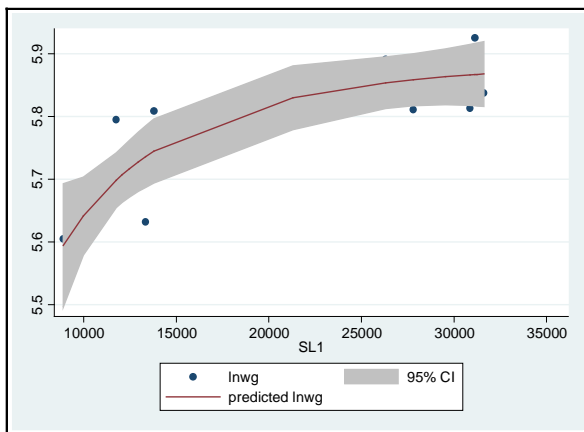


Figure 2: Predicted Wage Gap on Skilled Immigration in Manufacturing Sector

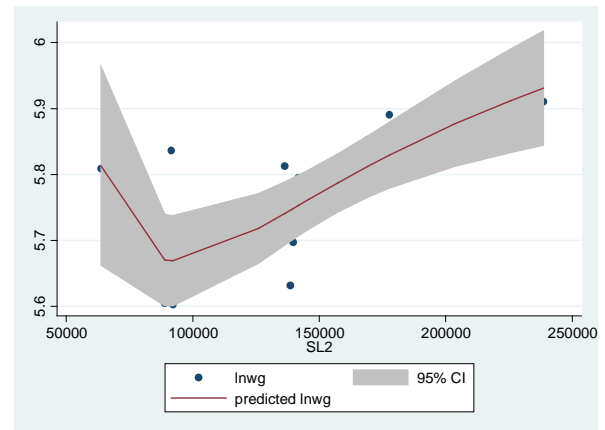


Figure 3: Predicted Wage Gap on Skilled Immigration in Innovative Sector

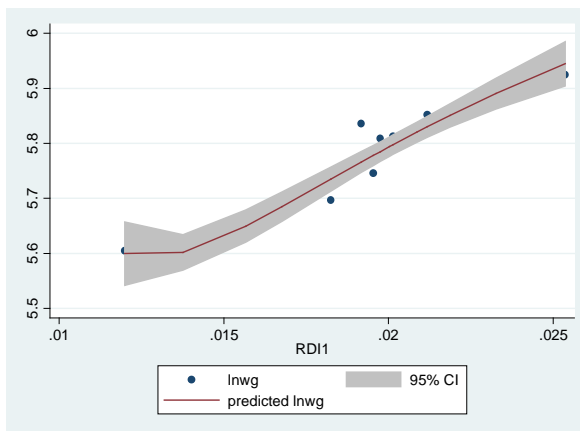


Figure 4: Predicted Wage Gap on R&D intensity per worker in Manufacturing Sector

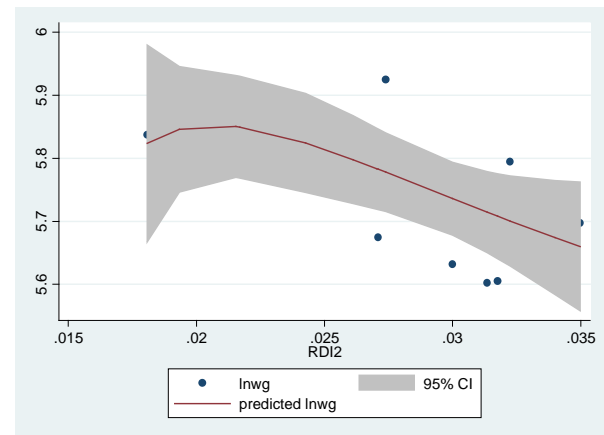


Figure 5: Predicted Wage Gap on R&D intensity per worker in Innovative Sector

Hence, it is difficult to establish a clear relation between skilled immigration and native wage inequality unless *other explanatory factors* are taken into account. Indeed, figure 4 shows that if the R&D intensity of the manufacturing sector increases alone, beyond a small range, this raises the native wage inequality steeply. However, if the intensity in the R&D sector rises it leads to a fall in the predicted native wage gap (figure 5). As mentioned before, in order to evaluate these independent relations in the presence of other factors, the simplest procedure is to use *interaction terms*. This should allow us to evaluate the role of one independent variable on the target variable given an

average level of the *other independent variable interacted with*. Consequently, we use $(S_{L1} * RDI_g)$ as interaction between skilled immigration in the manufacturing and the R&D intensity gap and predict the impact for the native wage gap in figure 6. Similarly, we use $(S_{L2} * RDI_g)$ as interaction between inflow of skilled immigrants to the R&D sector and the intensity gap, and relate the same to native wage gap in Figure 7.

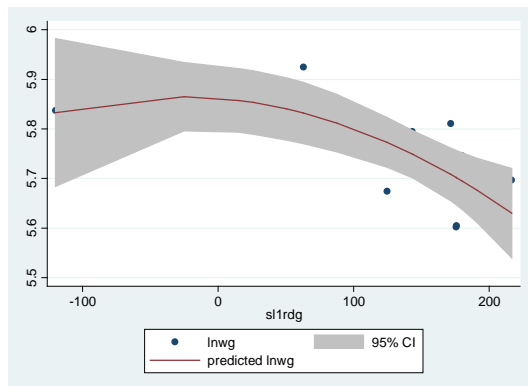


Figure 6: Predicted Wage Gap for interaction between skilled immigration in manufacturing and RDI_g .

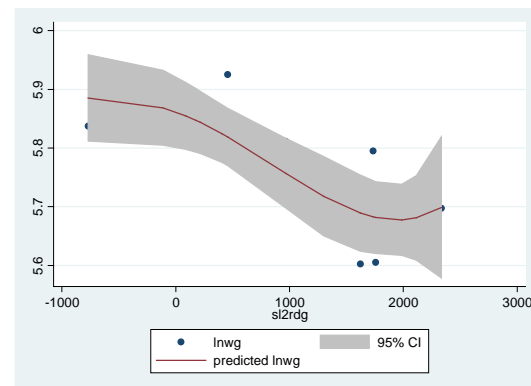


Figure 7: Predicted Wage Gap for interaction between skilled immigration in R&D and RDI_g .

It is possible to infer that given the average number of skilled immigrants in manufacturing, as R&D intensity gap between the two sectors increases, wage gap falls unambiguously. This is briefly reminiscent of figure 1, wherein the RDI_g has overwhelming impact on wage inequality for an average skill migration. More importantly, however, figure 6 also posits that a rise in skill migration to manufacturing could lead to a modest fall in native absolute wage gap if the R&D intensity is held at a positive average. Similarly, in Figure 7, the native wage gap falls subject to a rise in skill migration to the R&D sector for an average R&D gap over a much bigger range as compared to Figure 6.

Thus, contrary to many previous studies arguing that skilled-to-unskilled wage gap responds positively to uptake of better technology in the developed world, and/or inflow of relatively unskilled immigrants in such countries (*viz.* Berman *et al.*, 2003, Borjas 2014), we show that skill immigration to high tech sectors of USA should ideally reduce the absolute wage gap (or the ratio) between native skilled and unskilled workers.

To be precise, if skilled immigration is channelized into the innovative sector, and that the R&D intensity of the innovative sector rises much more than the general manufacturing sector, the native wage gap is most likely to fall. In a different context, the complementarity between high-skilled and low-skilled workers seem to rise in technologically advanced sectors (see Aghion *et al.*, 2017), thus improving the productivity and pay of the low-skilled more than proportionately. Earlier, Ottaviano *et al.* (2012) used a data-preferred nested-CES model to show that immigration has a small positive impact on the wages of native workers with no high school degree (i.e. unskilled). It also had a small positive effect on average native wages, but non-significant effect on the wages of native skilled personnel.

Since we are constrained by the availability of relevant data beyond a handful of data points, we present a simple correlation coefficient between skilled-unskilled wage gap and the R&D intensity gap. This is found to be negative and significant (Table A.1 in the appendix). However, in order to capture the linear interdependencies between aforementioned variables, the basic Vector AutoRegression (VAR) model is used where each variable forms an equation to explaining the evolution based on its own lagged values, lagged values of other variables and the error term.

5.3 VAR Model Specification:

In view of the aforementioned variables, the following equations denote how RDI_g and the (log of) wage gap are functionally related. This is repeated for two interaction terms, sl_1*rdi_g and sl_2*rdi_g (see Table 1):

$$\ln wgt = \alpha_0 + \alpha_1 \ln wgt_{t-1} + \alpha_2 \ln wgt_{t-2} + \beta_1 RDIg_{t-1} + \beta_2 RDIg_{t-2} + u_t \dots\dots\dots (1)$$

$$RDIgt = \gamma_0 + \gamma_1 RDIg_{t-1} + \gamma_2 RDIg_{t-2} + \delta_1 \ln wgt_{t-1} + \delta_2 \ln wgt_{t-2} + v_t \dots\dots\dots (2)$$

Here, the notations have their usual meanings with current period value (t), lagged value for one year ($t-1$) and lagged value for two years ($t-2$). The descriptions of the variables as well as the descriptive statistics are available in Appendix A.2.

Table 1: Results of Basic VAR model with Interaction Terms

	col1	col2	col3	col4
Variables	rdi_g	rdi_g*sl1	rdi_g*sl2	lnwg
rdi _g L4.	5.923 (4.03)	56.002 (39.82)	71.78 (48.84)	-124.8 *** (27.18)
rdi _g *sl1 L4.	-0.213 (0.534)	-2.21 (5.28)	-2.46 (6.481)	11.60*** (3.606)
rdi _g *sl2 L4.	-0.333 (0.4208)	-2.981 (4.156)	-4.124 (5.098)	1.03 (2.83)
lnwg L4.	-0.056** (0.0194)	-0.511** (0.191)	-0.647** (0.235)	0.105 (0.131)
Cons	0.325** (0.113)	2.974886	3.76 ** (1.374)	5.25*** (0.764)
Observations	11	11	11	11

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

Source: Author's Own Calculation

Table 1 indicates that a 1percentage point positive shock to the four-year lagged value of gap in research and development expenses across manufacturing and innovation sector *lowers* wage gap significantly (at 1% level). The reverse is also true, but rather weak apart from the fact that this is only a motivational exercise offering some direction only. The empirical result needs cautious interpretation owing to fairly limited data points between 2002 and 2016. Indeed, we have applied lag selection criteria before conducting a simple VAR with logarithmic values of the variables, and we find that AIC, SBIC, HQIC indicate the choice of a 4-year lag (see appendix). Consequently, the VAR model is based on responses with 4 period lags subjected to an impulse at the beginning of the period. The impulse response functions in figure 8 (panel 1) shows the 4-year lagged effect of an impulse in R&D gap between the sectors on the log of wage inequality between skilled and unskilled native workers. This is the most crucial result following from Table 1, displaying a fall in the native wage gap owing to a rise in R&D expenses incurred by the innovation sector (implying a rise in R&D gap).³¹ Since the interaction term for R&D gap and skilled labour inflow in R&D sector (rdi_g*sl2) has non-significant

³¹ We do not report Granger causality between such variables (available on request).

response from log of wage gap, the aforementioned negative effect clearly dominates. In comparison, the interaction term between R&D gap and skilled labor inflow in the manufacturing sector ($rdi_g * sl1$) generates a positive and significant response from the log of wage gap but not as strongly. Therefore, overall, this brief exercise shows that greater R&D activities destined to the innovation sector lowers the wage gap between native skilled and unskilled workers for a suitable choice of lag as discussed above. The inflow of skilled workers into the innovation sector maintains this relationship unambiguously. This exercise shows that—in keeping with the theoretical premise—to be successful practically, immigration policy should consider functional interdependence between less-skilled as well as the highly skilled migrants (Czaika 2018). That will reduce skill premiums and prevent labor market disruptions.

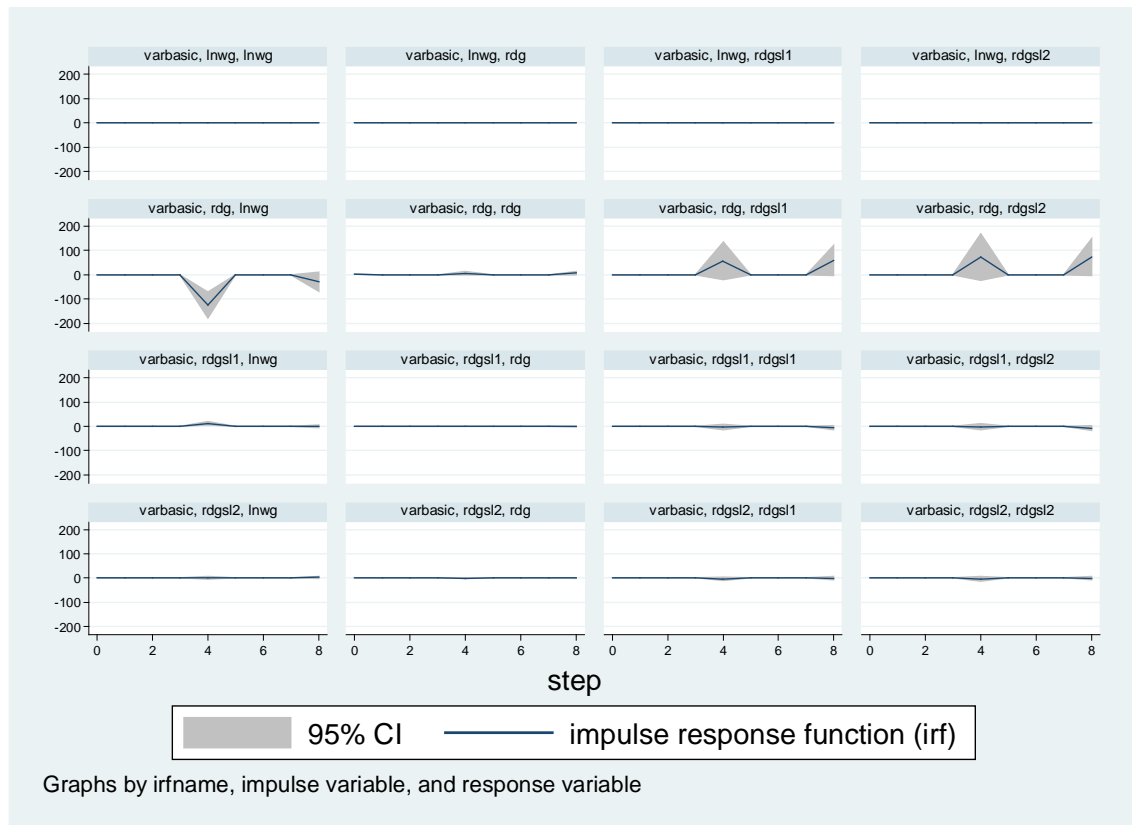


Figure 8: Impulse Response Functions for the VAR model

6. Policy Insights and Concluding Remarks:

The complex issues and debates about immigration reforms involving skilled migration calls for a nuanced evaluation of policies relevant for immigration boosting innovation, and its impact on returns to occupational categories. In fact, the concern about job losses in advanced economies are centered on the debate about impact of automation and innovation ('new' technology) on job losses, creation, and occupational non-routine cognitive vis-à-vis routine manual or cognitive types with exaggerated fear (Salvatore 2019, Shiller 2019). The analytical model—based on background stylized evidences and current spate of debate about restrictions on immigrations—shows that apprehension about adverse impacts on wage gap in the rich host economies (either in EU or USA) is not well founded. Under alternative scenarios about migration of high skilled talents into skilled and innovative sectors, we argue that policy debates about migration-induced wage inequality should consider the contribution of innovative sector in cost-share of different sectors of the economy. In other words, complementarity among innovative and manufacturing production sectors enable reducing wage gap. The results corroborate the fact that relative shares of R&D inputs and skilled vis-à-vis unskilled workers matter for direction of movement of wage inequality between skilled and low-skilled workers; in other words, the apprehension and hence, the policy debates in the US that wage inequality will worsen following high skilled migration ignore the important aspects of how innovative sectors could benefit the low skilled manufacturing with a conducive spillover effect on the unskilled wage. In particular, the results point out that if R&D-input—innovated via talent migrants in the innovative sectors—is important in production (i.e., higher relative cost-share than that in the skilled sector) for the unskilled manufacturing sector, wage inequality decimates. Even with homogenous skill types used in both innovative and skilled sectors, skilled immigration in R&D sector will lower wage inequality in fairly general setups, irrespective of different R&D-input types and immigrant skill types. Mayda et al. (2017) has shown that restrictive immigration policy via cutback in H-1B visa does not increase employment of US workers. The results underpin the policy insights that a balanced and pragmatic approach weighing skilled and less-skilled migrants are necessary for a well-guided immigration reforms to be fruitful.

For immigration to be inclusive, contributions of high skilled talent for innovation should have induced spillover effects. In other words, the share of output of innovative sector is critical for unskilled to benefit. Via R&D done by talented migrants' innovativeness, the unskilled productivity improvement results in increases in their wages, resulting in reduction of the existing wage gap. Therefore, unanimous across the board ban on immigration might be counter-productive unless direct and indirect spillover potentials are neglected. It is prudent to use the foreign talents for productivity-enhancing sectors by dint of their innovation potentials. Under the aegis of globalization, the policy resilience in the economy could be built by channelizing the pool of foreign human capital in high value-added sectors that, without disruption, help the unskilled to make immigration inclusive. In keeping with the background facts and literature (vide section 2), this result confirms our conjecture. Although our analysis is predominantly focusing on US case, role of skill composition of immigration and its effects on innovation is significant in Europe as well as in other advanced nations. For example, Ozgen et al. (2017) presents evidences that for a panel of 170 regions in Europe (NUTS 2 level), average skill levels of the migrants affect patent applications significantly. Same for New Zealand (McLeod et al. 2014).

In essence, this implies that without eviction or blocking of skilled vis-à-vis unskilled workers, the rigid immigration policy could be made inclusive by utilizing high skilled immigrants in STEM employment and using the outcomes for other sectors that employ low skilled labor and immigrants, where participation of foreign workers improve welfare as policies remove impediments (Shimada 2005, Cobb-Clark 1998, Salvatore 2017). If the employment of foreign-born skilled workers translates into enhanced innovation and growth without crowding-out of native workers (skilled and unskilled), host country welfare will certainly improve. This research has a wider connotation for policy dialogues on migration, innovation and productivity. Drawing on survey of entrepreneurs, Brown et al. (2019) discusses that foreign-born entrepreneurs has 'sizeable advantage in innovation' in high-tech sectors. As the current spate of slowdown and productivity decline hampers US economy, innovation (alike digital revolution) is necessary for revival prospects. Skilled immigrants could contribute to innovation as well as develop its 'close cousin' entrepreneurial talents with positive impact on labor market

(Gordon and Hassan 2019, Kerr 2019a&b). As Summers (p. 543, 2018) has mentioned: “the current anti-immigrant attitude threatens our global standing. We have long been the country in the world renowned for providing opportunities to talented and perseverant foreigners to build better lives for themselves and their families. This has been a mutually beneficial relationship: in turn, immigrants have innovated and invented—creating jobs and helping our economy flourish.” Therefore, making immigration policy conducive for innovation policy and entrepreneurship is necessary for coping with ‘new’ technology, shaping ‘future of work’, and avoiding productivity slowdown.

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Appendix:

(1) Notations used

Time Period: 2002-2017 (16 Years)

Variables :-

W_S : Skilled Wage (Average) for Natives in US

W_U: Unskilled Wage(Average) for Natives in US

W_g : Wage Gap (Skilled-Unskilled) [**W_S - W_U**]

SL₁: No. of Skilled Immigrants in Manufacturing Sector (NAICS Code:31.32,33)[No. of H1B visa holders coming in manf.cos.]

SL₂: No. of Skilled Immigrants in Innovative Sector (NAICS Code:54) [No. of H1B visa holders coming in innovative cos.]

T_s : Total no. of skilled Immigrants in US (Total no. of H1B Visa holders in a year)

RD_M: Domestic R&D Spending by Manufacturing Companies (In Million \$US)

E_M: Domestic Employment by Manufacturing Companies

RD_I: Domestic R&D Spending by Innovative Companies (In Million \$US)

E_I: Domestic Employment by Innovative Companies

RDI₁: R&D Intensity per worker in Manufacturing Cos (In Million \$US) [**RD_M/ E_M**]

RDI₂: R&D Intensity per worker in Innovative Cos (In Million \$US) [**RD_I/ E_I**]

RDI_g: R&D Intensity Gap between two sectors [**RDI₂- RDI₁**]

(2) Selection-order criteria

Sample: 2006 - 2016

Number of obs = 11

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	170.693				8.1e-19	-30.3079	-30.3991	-30.1632
1	197.526	53.666	16	0.000	1.5e-19	-32.2775	-32.7335	-31.554
2	.	.	16	.	-1.5e-45*	.	.	.
3	1336.61	.	16	.	.	-235.021	-236.024	-233.429
4	1459.81	246.39*	16	0.000	.	-257.42*	-258.423*	-255.828*