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Diversity in Segmention. Patterns of Immigrant Competition in US Labor Markets

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Abstract

Competition between immigrant and native workers takes place in labor markets that are segmented along various, often unobservable dimensions. It is desirable to measure the extent to which native workers are effectively shielded from competition by immigrant workers by virtue of such patterns of segmentation. This paper proposes measures of group differences in labor market segmentation on the basis of incomplete data, such as can be obtained from the US Census. These measures are derived from a general class of models of labor competition in the Smithian tradition. The observed wage distributions of native and foreign-born workers in the United States (at the national and metropolitan level) can be approximated remarkably well with this class of model, suggesting that a parsimonious account of wage inequality is feasible.

Keywords— Immigration, labor market competition, segmented labor markets, wage inequality, statistical equilibrium ***JEL Codes***— J15, J31, J42, J61

1 Introduction

The competition of immigrant and native workers has been a perennial theme in the economic literature (e.g. Ottaviano and Peri 2012; Borjas 2014; Card and Peri 2016; Dustmann, Schönberg, and Stuhler 2016). Generally, the focus is on immigration as a supply shock in labor markets and their impact on average wages for different categories of workers. Underlying this literature is a model that interprets observed average wages for different types of workers as the attained equilibrium between supply and demand. Interest centers primarily on whether changes in the supply of a particular type of labor are detectable in these market clearing wages, and whether there are disemployment effects for native workers.

This paper argues for a less mechanistic interpretation of the competition between and among immigrant and native workers. Labor markets are subdivided into a myriad of niches or segments which allow for varying degrees of mobility. Natives and immigrants may differ both in their evaluation of job opportunities in different labor market segments, as well as their ability to realize those opportunities. The model presented in this paper can account for this type of heterogeneity, which may reflect institutional and informational barriers as much as employment discrimination. While immigrant and native workers compete in the same labor market, there may be substantial differences in their access and willingness to enter different labor market *segments*.

The information contained in population surveys is generally insufficient to measure all aspects of labor competition unambiguously. This concerns in particular some of the important behavioral differences between immigrants and natives in the labor market. In a first section, we outline the class of Smithian models of labor market competition and show how it can be used to make minimally biased inferences about the unobserved behaviors of the different groups. In the second section, we show how our model class can be applied to Census data in the US. Despite its simplicity, the framework can robustly account for observed differences in wage distributions between native-born Whites and Blacks as well as native- and foreign-born Hispanics. In a final section, we apply the framework to regional labor markets and relate the results to the concentration of different ethnic groups in each location.

2 Measuring Labor Market Competition using Incomplete Data

Population censuses are our most extensive data source on labor market outcomes. Consequently, labor force surveys and population censuses have been the basis of most research in empirical immigration economics. Census data is primarily designed to estimate the size of different subpopulations, including immigrants from different regions of origin, and a small set of their socioeconomic characteristics.[1] While this allows some stratification of the national labor market, notably by skill level (Borjas 2003) and region (Basso and Peri 2015), the information necessary to measure labor market competition unambiguously is missing.

The approach developed in Wiener 2018, itself based on Scharfenaker and Foley 2017, offers a transparent and minimally biased measure of labor market competition in this incomplete data setting. The methodological point-of-view underlying this argument is sufficiently different from standard economic practice to warrant a brief recapitulation.

As discussed above, survey data represent a snapshot of labor market *outcomes* at a given point in time, without detailed information on individual trajectories. In such circumstances, theoretical considerations are usually drawn upon to complement the observed data. While economic theory can provide some broad guidelines about causal relationships in social interaction settings,

[1] There are legitimate concerns about the ability of government surveys to reach immigrant populations, in particular households with undocumented members. Even though the Census Bureau attempts to give greater weight to respondents from populations with low response rates, it does so on the basis of estimated total population sizes that may be inaccurate. However, this type of incompleteness is not the focus of this paper.

there is very little consensus on the specific micro-kinetic laws governing behavior. Rather than proposing a specific set of behavioral rules which are then exposed to falsification along the lines of Friedman 1953, the approach followed here attempts to identify the least restrictive, most general *class of models* still consistent with the observed data. Rather than claiming to have identified the uniquely correct model of labor market competition, the goal is rather to provide intermediate results that help focus future research.

This goal is achieved by deriving a set of *probabilistic* associations between observed wage outcomes and the unobserved competitive behavior, following a broadly Smithian vision of competition. A range of specific micro-kinetic models of worker mobility and competition will be compatible with the joint probability distribution proposed here. The model class is defined by a set of constraints on *moments* of the joint distribution, which embody the common Smithian theme of competition as a negative feedback mechanism (Foley 2006).

2.1 Maximum Entropy Approach

The problem of inferring information about the unobservable dimensions of labor market competition on the basis of incomplete data is approached using an axiomatically well-founded information-theoretical tool. The Maximum Entropy (MaxEnt) approach, developed in a series of contributions by Edwin Jaynes (Jaynes 1957; Jaynes 2003), can be summarized most immediately as a heuristic for choosing a probabilistic model that incorporates any prior information about a system under study, while imposing no additional hidden or extraneous assumptions. In economic systems, this prior knowledge includes in particular information about the structure of incentives and constraints faced by the interacting agents (Scharfenaker and Foley 2017).

Entropy is a measure of uncertainty, or equivalently of the expected amount of information conveyed by observing the outcome of an experiment. Intuitively, the surprise at observing an outcome k should depend negatively on its probability of occurrence p_k. A rare event should surprise an observer more than a common event. The negative logarithm of the probability of observing the event, $-log(p_k)$, represents this idea. The base of the logarithm defines the unit for the measure of uncertainty, such as *bits* for a base of 2. As an example, consider the experiment of flipping a biased coin with a prior probability of coming up head $p_h = 0.9$. The amount of information conveyed by an outcome "tail" is $-log_2(0.1) \approx 3.3$ bits.

On the other hand, the *expected* surprise value of a rare event before the outcome is known should be quite low. The ex-ante uncertainty about the outcome of flipping the biased coin is much lower than the uncertainty for a fair coin. Jaynes 2003 has shown that the unique measure of expected surprisal (or observer uncertainty) that respects a small set of axioms is Shannon's entropy:

$$S(p) = -\sum_k p_k \, log(p_k) \tag{1}$$

The goal of inferring a probability distribution over possible outcomes without imposing any hidden assumptions can be seen to be tied to maximizing the uncertainty (1) of the candidate distribution. The MaxEnt principle directs the researcher to express her theoretical expectations in the form of constraints on moments of the probability distribution, and then select the least committal, most uncertain distribution that still satisfies the constraints.

Conversely, Jaynes 2003 has shown that given a set of constraints, realized distributions in systems with many degrees of freedom are overwhelmingly more likely to be near the entropy-maximizing distribution. This result has generated a research agenda of identifying distributions of social outcomes that show some structure and stability over time and interpreting them *as MaxEnt distributions*. If a candidate functional form for the observed distribution can be found, the subsequent step is to deduce the set of constraints subject to which this candidate distribution would be entropy maximizing.

These constraints to the MaxEnt program constitute in effect the class of models that are consistent with the evidence. While it may be possible to devise more elaborate micro-level models, they must imply the same set of constraints on the moments of the joint probability distribution. Since the evidence does not support further distinctions among potential micro-level models, parsimony would suggest reporting the constraints directly. In economics, recent work has applied this particular approach to the study of profit rates (Scharfenaker and Semieniuk 2016), wages (Schneider 2013), the growth rates of labor and capital productivity (Yang 2018), and Tobin's q (Scharfenaker and dos Santos 2015).

3 Smithian Class of Labor Competition Models

The Smithian theory of competition conceives of a process of ceaseless interactions among workers and employers, both conditioned by and shaping the aggregate wage distribution. Workers respond to wage signals by entering or leaving particular labor market segments. In the process, entering workers will tend to place downward pressure on niche wages and vice-versa for leaving workers, thereby reducing the wage differentials that gave rise to the mobility in the first place. The individual and uncoordinated entry/exit behavior of workers leads to an organized and predictable distribution of wage rates as an unintended aggregate outcome.

From the information-theoretic point of view, the mechanism of competition conveys information about wage outcomes by preventing them from straying too far from a common center of gravity. The amount of uncertainty removed by the competitive process is a measure of its intensity. If a single wage prevailed across the entire labor market, this model would suggest that the market was perfectly competitive in the sense of standard economic theory. On the opposite end of the spectrum wages would be completely disorganized. A rational observer would, when asked to predict the wages of a particular worker, merely pick any positive number at random. In this situation, Smithian competition provides no information about wage outcomes because it is inoperative. The Smithian class of models would interpret this situation to be one of complete segmentation, with no mobility between the labor market niches. The observed marginal wage distributions for the US economy are unsurprisingly between these extremes (Wiener 2018).

3.1 Quantal Response Statistical Equilibrium Model with Homogeneous Agents

We review here the logic of the Quantal Response Equilibrium model in labor markets, and develop its extension to heterogeneous workers. For a detailed discussion on the implications of the QRSE model to labor market analysis, the interested reader is referred to Wiener 2018.

Let (w, a) be the state variables of the system, corresponding to wages (observed) and entry-exit behavior (unobserved). The Quantal Response Statistical Equilibrium in labor markets is the joint frequency distribution $f(w, a)$ that has maximum entropy subject to two substantive constraints. These constraints represent a theory of competition that links the entry-exit behavior of agents to the wage outcomes.

Workers respond to differences between a segmental wage and a reference wage μ by entering or leaving a particular labor market segment. It is common practice (e.g Keane, Todd, and Wolpin 2011; Kennan and J. R. Walker 2011) to model decisions of this type by stipulating that workers will choose the alternative with the higher payoff - in this case represented by the difference $(w - \mu)$. Since such a model specification could fit no real-world data (in which dispersion is the norm), random errors are added to the payoff. The particular distribution of errors is generally chosen for compuational convenience, or by reference to a law of large numbers.

A more psychologically convincing derivation is suggested by the rational inattention framework (Sims 2003; Matějka and McKay 2015). In this perspective, the decision-making process is conceived of as a communication channel in the sense of information theory. The typical agent receives signals such as the wage rate through a channel with unknown but finite capacity, which is interpreted as the utility cost of processing the signal. Both physiological limitations as well as efficiency considerations lead to the prediction that only limited resources will be allocated to information processing. This assumption is enough to predict a behavioral response that corresponds to the well known logit or quantal-response pattern. Formally, the agent chooses the mixed strategy $f(a|w)$ that maximizes her expected utility, subject to a lower bound on the entropy of the strategy:

$$
\begin{aligned}
\max_{\{f(a|w)\geq 0\}} \quad & \sum_a f(a|w)(w-\mu) \\
\text{s.t.} \quad & \sum_a f(a|w) = 1 \\
& -\sum_a f(a|w) log\left(f(a|w)\right) \geq S_{min}.
\end{aligned}
$$

The predicted mixed strategy takes the inverse-logit form:

$$f(enter|w) = \frac{e^{\frac{w-\mu}{T}}}{1+e^{\frac{w-\mu}{T}}} \ \forall w \tag{2}$$

Note that (2) is also the prediction of an observer whose only knowledge about the decision-making process is that the expected payoff is finite (Wolpert and Leslie 2012).

As an unintended social consequence of their action, entrants tend to lower wages in their target niche (and vice-versa for leavers), thereby limiting the wage differentials that gave rise to the action in the first place. This feedback mechanism is represented in a constraint on the difference between the expected wage of entrants and leavers:

$$f(enter)E(w|enter) - f(exit)E(w|exit) \leq \delta \tag{3}$$

As discussed above, if competition imposed no structure whatsoever on the system, the wages in advantageous labor market segments would tend to be infintitely greater than those in disadvantageous segments. The intuition behind (3) is that competition limits this divergence to some unknown but finite amount δ.

3.2 Labor Market Competition with Heterogeneous Workers

The typical agent assumption in the standard QRSE model, although much less restrictive than the “representative agent” of economic lore, has some undesirable implications. The quantal entry/exit behavior is capable of representing the uncertainty of agents in responding to economic signals, or more likely our uncertainty as observers about their decision-making process. In either interpretation however, the model relies on a uniform “reference wage” below which workers tend to leave jobs, as well as a single behavioral temperature. It would be preferable if this strict assumption could be relaxed.

Social identity plays a central role in shaping the experience of workers. We represent differences between groups of workers in terms of their average *behavioral* responses to labor market opportunities, as captured by group-specific decision temperatures T_m and reference wages μ_m. However, native and immigrant workers both are part of the same labor market, even though concentrated in different market niches. Therefore we keep the constraint that the expected wage of entrants, both immigrants and natives, exceeds that of leavers. This represents the notion that workers of all groups still compete in the same overall labor market, even if they differ in their access to different labor market segments and their willingness to accept low wage jobs. The assumption also appropriately reflects that we have insufficient information about specific patterns of cross-group competition.

Finally, we add a constraint on the proportion of agents of each type (8). We take the expected proportion of agents of each type to be equal to their observed proportion in our sample.

The Maximum Entropy program therefore looks like

$$\max_{(\{f(a,w,m)\geq 0\})} S(f(a,w,m)) \tag{4}$$

subject to

$$\sum_m \sum_a \int_{w=0}^{\infty} f(a,w,m)\,dw = 1 \tag{5}$$

$$f(enter)E(w|enter) - f(exit)E(w|exit) \leq \delta \tag{6}$$

$$f(enter|w,m) = \frac{e^{\frac{w-\mu_m}{T_m}}}{1+e^{\frac{w-\mu_m}{T_m}}}\ \forall(w,m) \tag{7}$$

$$f(m) = \frac{n_m}{\sum_j n_j}\ \forall(m) \tag{8}$$

After some manipulations (see appendix 8.1), we find that this maximization problem has a unique solution:

$$\hat{f}(w|m) = \frac{e^{S(f(a|w,m))}e^{-\beta\, tanh(\frac{w-\mu_m}{2T_m})w}}{\displaystyle\int_{w=0}^{\infty} e^{S(f(a|w,m))}e^{-\beta\, tanh(\frac{w-\mu_m}{2T_m})w}\,dw} \tag{9}$$

Equation 9 gives the form of each group-specific marginal wage distributions in the QRSE model. We can obtain a range of interesting conditional distributions from the rules of probability. In particular, we can find the joint distribution of wages and ethnicity as $f(w,m) = f(w|m)f(m)$ (where the $f(m)$ are set equal to the group proportions $\frac{n_m}{\sum_j n_j}$) and then the joint distribution $f(w,a,m) = f(w,m)f(a|w,m)$.

The MaxEnt distribution leaves $\theta = (T_m, \mu_m, \beta)$ undetermined. We estimate these parameters by considering (9) as the kernel to a multinomial likelihood of the observed frequency distribution given θ. The distribution is multinomial due to the discretization of the data in the binning process. Note that our data are on (w,m), while the action variable is unobserved. So we are fitting the observed distribution $f(w,m)$ using the predicted distribution $\hat{f}(w,m) = \hat{f}(w|m)\cdot f(m)$. Details of the estimation approach can be found in the appendix.

4 Competition among Broad Ethnic Groups in the National Labor Market

The US national labor market is characterized by significant cleavages along race and ethnic lines. Field experiments and audit studies reveal highly persistent discriminatory practices in hiring decisions (Bertrand and Mullainathan 2004; Quillian et al. 2017). Perhaps even more important in shaping divergent labor market outcomes between racial and ethnic groups is the cumulative impact of discrimination throughout the life course, such as in schools (Rosenbloom and Way 2004; Gilliam et al. 2016) and the criminal justice system (Council 2014).

Immigrants are entering this heavily segmented labor market at different levels. For the purposes of this study, we focus on the numerically and politically signficiant group of Hispanic immigrants. [2] Interest centers on the degree to which Hispanic immigrants compete with native-born Hispanic, as well as non-Hispanic black and white workers.

Figure 1 shows the observed distribution of wages for different race and nativity groups for each census year (solid). Overlaid are the fitted wage distributions from the QRSE model of labor competition (dashed). It is worth emphasizing that there are only two additional degrees of freedom added to the model with each group.

Despite this parsimonious setup, the model fits the wage distributions remarkably well (Figure 2). The Informational Distinguishability (ID) index proposed by Soofi, Ebrahimi, and Habibullah 1995 gives a useful quantification of the goodness-of-fit between the observed and predicted distributions [3]. We may think of models as devices to compress, and hence efficiently communicate economic data. From this point of view, the ID index represents the share of information left to be learned about wage outcomes beyond the Smithian theory of competition. For all but the foreign-born Hispanic group, the model accounts for around 98% of the information contained in the group-specific wage distributions. Hispanic immigrants are so strongly concentrated in low wage jobs that the model strains to fit the extreme peakedness of the wage distribution. However, even here the QRSE model still leaves only about $3-5\%$ of wage information unexploited.

Figure 3 shows the trends over time for the estimated QRSE parameters together with the average wage ($\bar{w}_m$) in each group. The estimates reveal a hierachy in which Whites have the highest behavioral temperatures (T_m) as well as reference wages (μ_m), and hispanic immigrants have the lowest. The values for Blacks and native-born Hispanics are close together, with μ_{black} somewhat

[2] Hispanic immigrants are those born abroad of either self-described (in survey year 1980 and later) or imputed (1970)"Hispanic origin" (for details see Ruggles et al. 2015). We exclude those born to American citizens abroad, a group whose immigration experience is sufficiently unique to require separate treatment.

[3] The index is defined as $ID(p,q) = 1 - e^{-D_{KL}(p||q)}$, where $D_{KL}(p||q) = \sum_k p_k \cdot log\left(\frac{p_k}{q_k}\right)$ is the Kullback-Leibler divergence (also known as relative entropy) between the predicted and observed distributions.

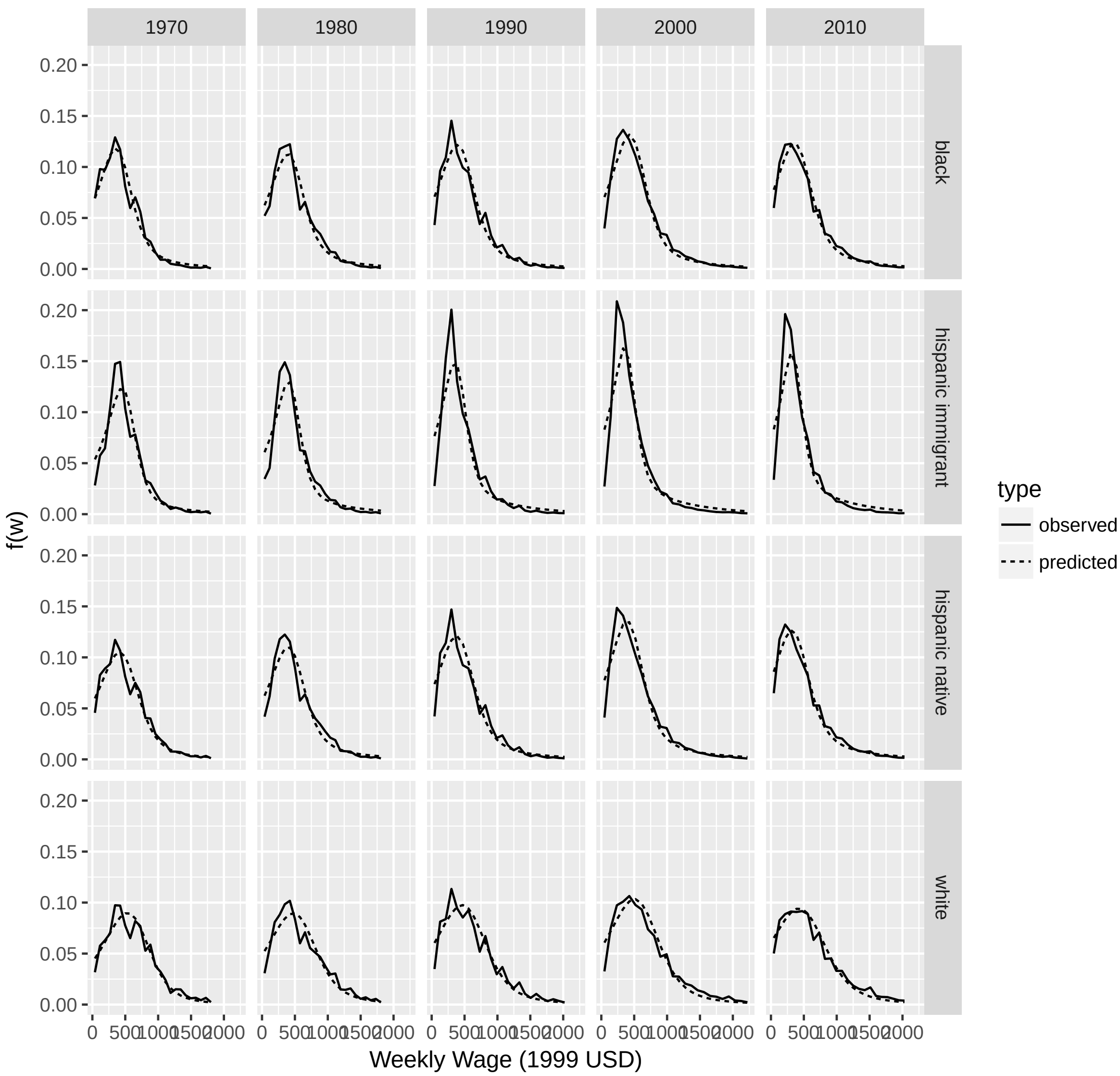

Figure 1: Observed (solid) and fitted (dashed) wage distributions, estimated jointly for all ethnicity groups using the QRSE model. 1970-2010 Census and ACS data.

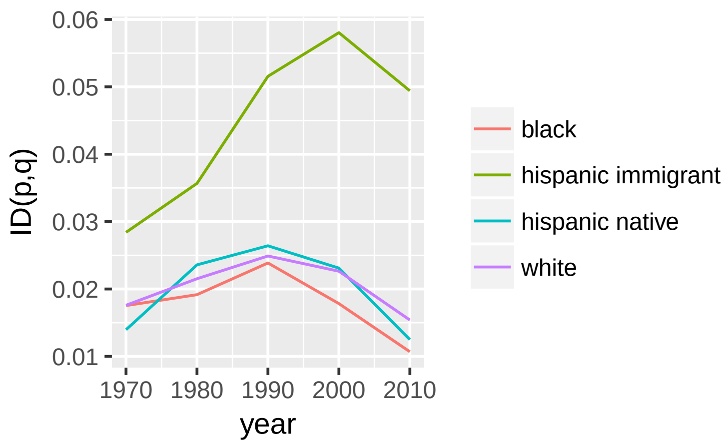

Figure 2: Soofi's Informational Distinguishability / goodness of fit measure for the jointly estimated QRSE model, by Ethnicity. 1970-2010 Census and ACS data.

higher than $\mu_{native,hisp}$ after 1980.

These results tell us about the responsiveness - and ability to realize - job opportunities for each ethnic group. Hispanic immigrants for example processes wage information around rather low wage levels very quickly, shifting into and out of jobs as wage conditions change. With higher wages, there is no behavioral change because any job would very likely be accepted. Notice however that such high-wage job opportunities come around extremely rarely for Hispanic immigrants, as can be seen from their low average wage and rapidly decreasing observed frequencies as wages increase (Figure 1).

In the Smithian models of competition, workers make their decision to compete in a particular niche of the labor market on the basis of a comparison between the (expected) niche wage and a reference wage. For Hispanic immigrants, this reference wage is likely at least initially tied to their region of origin. If an immigrant remains attached to the community of origin, she will be more willing to accept wages at the lower end of the host society's wage distribution (Stark and Taylor 1991). The reference community may however change as emigrated members of the household begin to look to the host community as a reference group. Over time, the reference wage may come to resemble that of the host country.

Consider the results for native-born Hipanic workers, some of whom may be second and third generation immigrants. We might interpret their higher reference wage as the outcome of "assimilation" towards the level of other native-born workers. This group no longer compares wage prospects of job opportunities to the potential earnings "back home", having instead partially converged in their evaluation to other native-born groups. The behavioral temperature $T_{native,hisp}$ has also increased, suggesting a decline in the degree of segregation of Hispanics

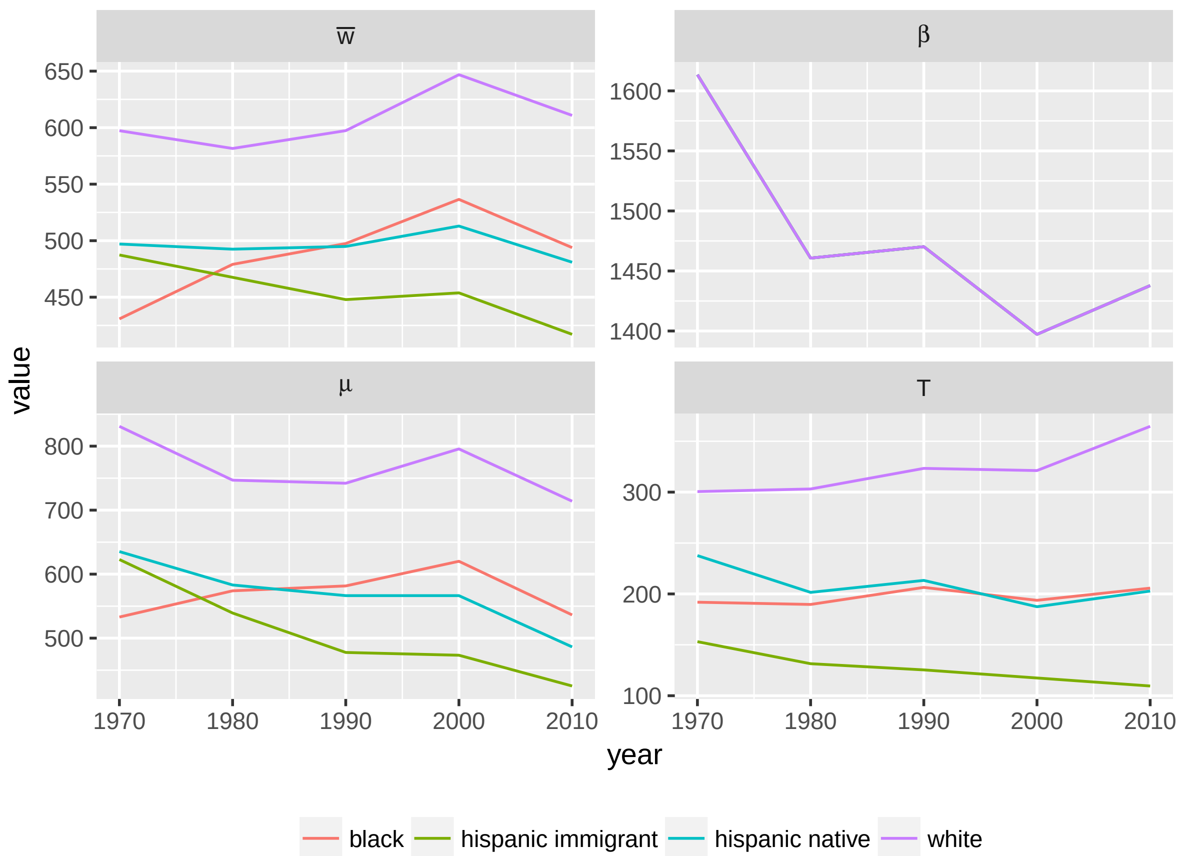

Figure 3: Average Wage and Estimated QRSE Model Parameters by Ethnicity. 1970-2010 Census and ACS data.

within the labor market.

Black workers have seen an improvement of their average and reference wages relative to Hispanic workers over the course of the last three decades of the twentieth century. Interestingly, the behavioral temperatures of native-born Blacks and Hispanics are almost identical throughout the period of analysis, suggesting that they face similar degrees of mobility restriction but at somewhat different wage levels. Finally, there has been almost no improvement in the position of Blacks relative to Whites according to the QRSE measures, certainly in the decades after 1980.

The behavioral predictions of the QRSE model allow us to indentify what might be called the "competitive reach" of each social group (see Figure 4). One summary measure is the wage level at which the vast majority of workers would enter a labor market segment. In 2000 for example, 99% of Hispanic immigrant workers would accept a weekly wage above 525 USD. The corresponding threshold was 877 USD for native-born Hispanics, 911 USD for Blacks and 1506 USD for Whites. This suggests that, even though Hispanic immigrant workers would be potential competitors in labor market segments with wages above 900 USD, they are likely not *effectively* competing for the same jobs, since they are barely represented in higher wage brackets.

Returning to the national US labor maret as a whole, there appears to be a decline in the estimated β, the Lagrangian multiplier associated with the impact of competition on segmental wage rates (Figure 3). This parameter represents the entropy benefits of relaxing the constraint on the expected wage differential between entrants and leavers. In other words, β measures how much more uncertain (in bits) an observer would be about the wage outcomes of a worker if the effectiveness of competition was relaxed (if the "competitive gap" δ was increased by USD 1). Values of β close to 0 indicate that the contribution of the competitive feedback effect to the organization of wage outcomes (i.e. to the reduction of entropy) is small. A declining value of β therefore represents a decreasing impact of competition, increasing the gap between the expected wages of entrants and leavers.

At the same time therefore as group-specific measures of job mobility have diverged between social groups, the labor market as a whole has become less competitive. This is how the Smithian model class interprets the rise of wage inequality in the US over the past decades.

5 Labor Market Segmentation and Spatial Division of Labor

The degree of labor market segmentation likely varies across space. There is in particular a close connection between the segmentation of labor in the productive and reproductive spheres (Storper and R. Walker 1983; Harvey 2006), which expresses itself in the residential and employment clustering of ethnic groups. Cities such as New York and Los Angeles for example have been tra-

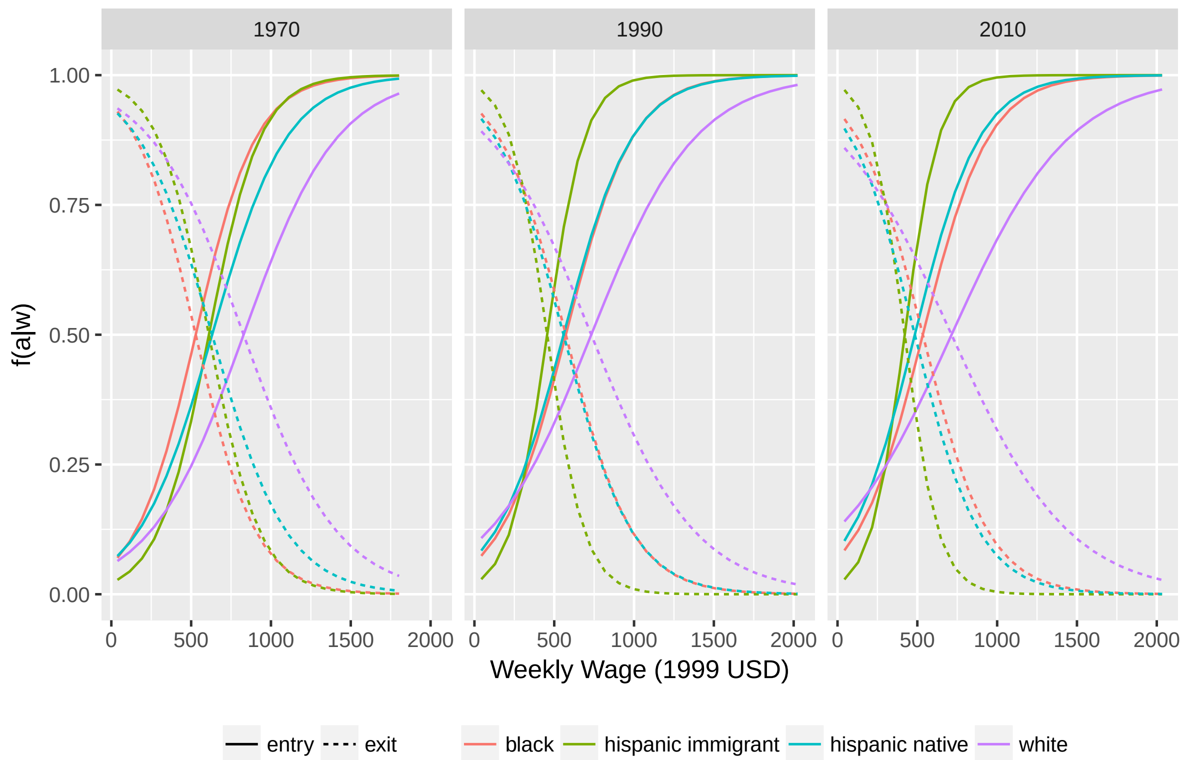

Figure 4: Predicted behavioral responses by race and ethnicity. Selected years, Census and ACS data.

ditional gateways for new arrivals into the US, among other reasons because immigrants could rely on extensive social networks in these locations. Beyond ethnic concentration, there is regional variation in industry structure and labor market policies that likely influences the relative economic success of immigrant and native population groups.

Recent work on inequality and labor market outcomes has made extensive use of variation among local labor markets in the US (Autor, Dorn, and Hanson 2013; Cadena and Kovak 2016). Here we follow the same approach of viewing local labor markets as "test tubes" exposed to different treatments. We use metropolitan areas as defined by the Census Bureau and to the extent that they can be identified in the public-use data. The consistency of this local labor market concept is limited, and the results should be considered as approximations (see appendix 8.2 for details). For this study, attention was restricted to metropolican areas with at least 1000 foreign-born respondents in our 1980 sample, which leaves 41 of the largest cities in the US. We exclude the 1970 census from our analysis, because the sample sizes are generally insufficient for analysis at the metropolitan area level.[4]

The Smithian model is estimated using two groups at the city-level, native and foreign-born workers, without further distinguishing ethnicity or region of origin. This increases the sample size available per groups. Later the results are complemented with information on the population composition in each city. Except for this change in the level of disaggregation by social group, the approach to estimating metropolitan area labor market segmentation remains the same as at the national level. See Figure 8 in appendix 8.3 for goodness-of-fit estimates.

5.1 Labor market segmentation in major US cities

Urban labor markets can be analyzed both in terms of their overall measures of labor market competitiveness and segmentation, as well as the extent to which the competitive behavior of foreign- and native-born workers differs from each other. Group-specific labor market segmentation between foreign-born and native workers is reflected in the Smithian class of models primarily in differences in the behavioral parameters T_m and μ_m, while the overall level of competitiveness in a labor market is measured by the β coefficient.

Figure 5 shows the estimated competitiveness β for each city over time. β is strongly negatively correlated with city-wide average wages, so that greater intensity of competition is associated with lower average income of workers. Since smaller cities tend to have lower average incomes, they have higher β values (Figure 9 in appendix 8.3). The Smithian model interprets the lower wage inequality in smaller cities as the outcome of more intense competition.[5]

[4] Detroit, although satisfying the inclusion criterion, is removed from the sample because the optimization algorithm fails to converge for this case.

[5] Our ability to identify any effects of population size is limited by the selection rule of focusing on metropolitan areas with at least 1000 foreign-born respondents.

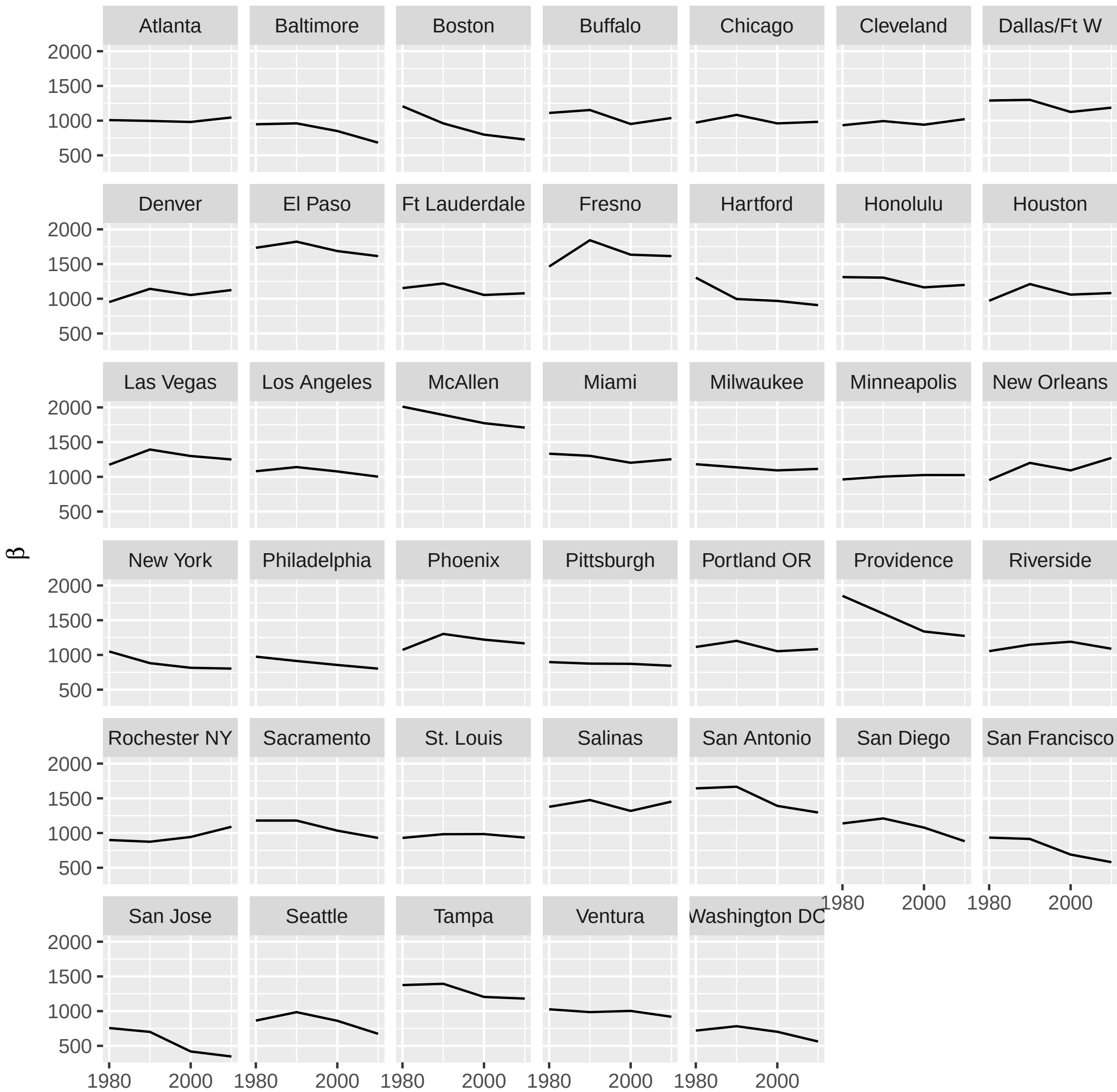

Figure 5: Competitiveness (β) estimates for major metropolitan areas. 1970-2010 Census and ACS data.

Figure 6 reveals a number of interesting features about the different competitive behaviors of the two groups. First, both the ratios of behavioral temperatures ($\frac{T_{imm}}{T_{nat}}$) and reference wages ($\frac{\mu_{imm}}{\mu_{nat}}$) are largely below 1. This indicates that for the most part, immigrants are responsive to wage differentials in a more narrow range and at lower overall wage levels than natives. Some exceptions are cities, such as Buffalo, Cleveland or Pitsburgh before the turn of the 21^{st} century, with a relatively small but increasingly more educated foreign-born population. Over time however, there is a clear movement towards the bottom left of the graph (which can also be observed in the left- and downward shifting dashed mean lines), suggesting a decrease in the similarity between foreign-born and native workers after 1980.

The second observation to be gleaned from Figure 6 is the positive correlation between the two behavioral ratios. This pattern reflects the much stronger positive correlation between μ_m and T_m for foreign-born workers than the native born. In other words, in cities where foreign-born workers have higher reference wages, they also tend to have greater behavioral uncertainty. The same is true for native workers, but to a smaller extent. Figure 7 reveals that there is a negative correlation between the ratio of behavioral temperatures and the level of competitiveness for foreign-born workers, but not for the native born. As labor markets get more competitive, the divergence between the behavioral uncertainty of immigrants and natives increases.

Figure 6 suggests a classification of cities according to the degree to which immigrants' competitive behavior differs from that of natives. Cities towards the bottom left corner, including Los Angeles, Houston and other prominent immigration destinations, have larger differences between immigrants and natives, both in terms of behavioral temperatures and reference wages. These cities tend to have larger shares of foreign-born as well as (native and foreign-born) Hispanic workers. Towards the top-right of Figure 6 are cities with fewer, but more highly educated immigrants.

6 Discussion

The application of the Smithian class of labor competition models to immigrant and native workers in the United States yields a series of interesting results that resonate with other findings in the literature on migration and labor markets.

The lower behavioral temperature of immigrant populations emerges as a robust finding, both at the level of the national labor market and within metropolitan areas. One possible explanation concerns the selectivity of migration, which would tend to favor workers that are particularly attuned to differences in conditions of employment. Stark 1984; Stark and Taylor 1991 have emphasized the role of relative deprivation, resulting from income comparisons within a reference group, for the decision to migrate. It seems prima-facie plausible that immigrants as a group retain some of the increased attention to income differentials in the destination country. As mentioned above, the reference community at least initially likely remains tied to workers of the same region of origin.

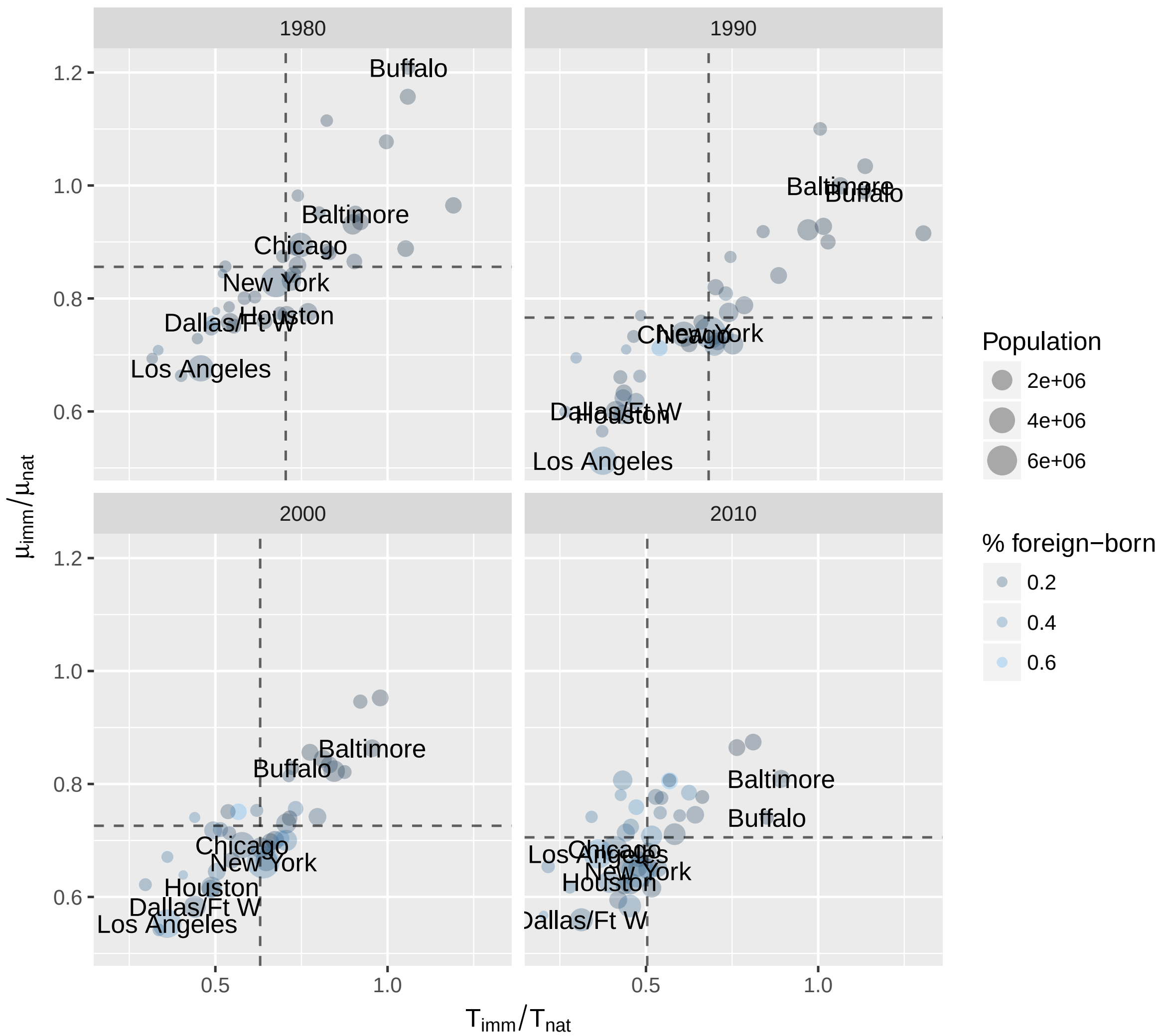

Figure 6: Foreign-born/native differentials of behavioral temperatures ($\frac{T_{imm}}{T_{nat}}$) and reference wages ($\frac{\mu_{imm}}{\mu_{nat}}$) for major metropolitan areas. Dashed lines are the unweighted sample means. 1970-2010 Census and ACS data.

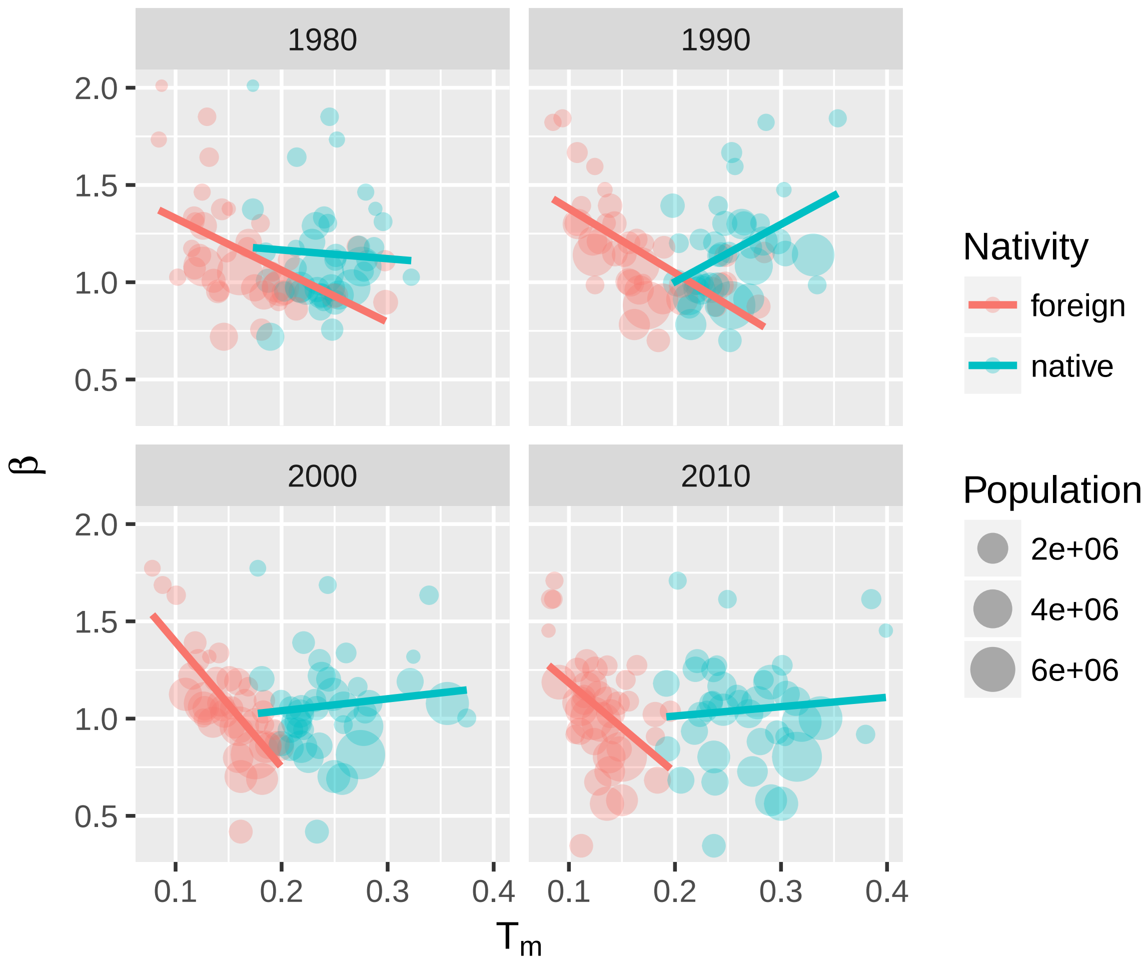

Figure 7: Competitiveness (β) against behavioral temperatures by nativity group for major metropolitan areas, with least-squares fit. 1970-2010 Census and ACS data.

The analysis of metropolitan-level labor markets further illustrates the distinct usefulness of the Smithian model. We might speculate for example that the negative correlation between the intensity of competition in an area and its population size reflects the Smithian tenant that the division of labor is limited by the "extent of the market" (Chpt. 3, Smith 1999). Because smaller cities provide less opportunity for the division of labor there are fewer market segments which would shield workers from competition. This finding is consistent with the "rank-size rule of income distribution" proposed by Korpi 2007, who argues that demand constraints in smaller cities prevent the emergence of more complex occupational hierarchies. Peters 2013 similarly finds that clusters of counties with greater income inequality are more populous and have higher median incomes compared to average inequality clusters. However, this interpretation fails for smaller cities with relatively high wage levels. San Jose for example, a highly unequal city with a sizeable high technology sector, is estimated to have a low intensity of competition but is small to medium sized relative to the rest of the sample.

The Smithian class of labor market competition models is arguably consistent with a range of more specific models proposed in the literature. In particular, the framework is agnostic with respect to the factors responsible for generating labor market segmentation. Jobs might differ in terms of the surplus available for bargaining, including due to imperfect competition in product markets and differential exposure to international competition (Akerman et al. 2013) (see Wiener 2018 for a more extensive discussion).

The heterogeneous agent version of the Smithian class of models allows to broaden the analysis of labor market segmentation to include inter-group dynamics, another aspect of labor competition that has received continued attention in the literature. Large differences in competitive behavior between groups, as can be found between foreign-born and native workers in major metropolitan areas in the United States, may for example reflect efforts of native workers to insulate themselves from the competition of immigrants, along the lines of split-labor market theory (Bonacich 1972). The same finding would also be consistent with the strategic use of social identity by employers to segment the workforce in the service of labor control and discipline (Gordon, Edwards, and Reich 1982). Both types of processes, exclusion by native workers and strategic segmentation by employers, are likely to be accompanied by self-reinforcing feedback loops through the use of social networks in hiring and job search (Waldinger and Lichter 2003).

7 Conclusion

The Quantal Response Statistical Equilibrium (QRSE) model, developed in Scharfenaker and Foley 2017, suggests a novel way of analyzing labor market competition between and among different social groups. Grounded in basic economic theory about the unintended consequences of individual behavior, the model proposes a parsimonious informational account of wage inequalities. Remarkably, with only two behavioral parameters per group and one market-wide parameter we can capture a large share of the information present in wage distributions. Furthermore, we can extract unobserved behavioral information from the observed wage distributions.

Above, we have investigated what this model reveals about the structure of labor market segmentation by ethnic group in the US. It shows heterogeneity in the job mobility behaviors, and in particular an increasing divergence of Whites and Hispanic immigrants over the past decades. African-Americans and native-born Hispanics show a very similar competitive reach in terms of the range of wages for which they are particularly sensitive to change. The process of assimilation is revealed in the extent to which native-born Hispanics compare wage opportunities to a higher reference value than immigrants. At the level of the US labor market as a whole, our model indicates a substantial decrease in the degree of competitive organization of wages.

A more varied picture emerges at the level of metropolitan labor markets. The QRSE model here directs attention to the relationship between market-wide characteristics such as the size and composition of the working population and the behavioral differences and competitiveness of the labor market.

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8 Appendices

8.1 Mathematical Appendix

The solution to the Maximum Entropy program (4-8) can be found via straightforward application of the Lagrangian multiplier method (see Kapur and Kesavan 1992, for details). First however, it is convenient to rewrite this problem somewhat. In particular, we absorb the behavioral constraint (7) into the objective function by decomposing the entropy:

$$\begin{aligned} S(f(a,w,m)) &= S(f(w,m)) + \sum_m \int_{w=0}^{\infty} (f(w,m)S(f(a|w,m)))\ dw \\ &= S(f(w|m)f(m)) + \sum_m \int_{w=0}^{\infty} (f(w|m)f(m)S(f(a|w,m)))\ dw \end{aligned} \tag{10}$$

where from constraint (7) we have

$$S(f(a|w,m)) = \frac{e^{\frac{w-\mu_m}{T_m}}}{1+e^{\frac{w-\mu_m}{T_m}}} log\left(\frac{e^{\frac{w-\mu_m}{T_m}}}{1+e^{\frac{w-\mu_m}{T_m}}}\right) + \frac{1}{1+e^{\frac{w-\mu_m}{T_m}}} log\left(\frac{1}{1+e^{\frac{w-\mu_m}{T_m}}}\right) \tag{11}$$

We also rewrite (6) as

$$\begin{aligned} f(enter)E(w|enter) - f(exit)E(w|exit) &\leq \delta \\ \sum_m \int_{w=0}^{\infty} (f(w,enter,m) - f(w,exit,m))w\, dw &\leq \delta \\ \sum_m \int_{w=0}^{\infty} (f(enter|w,m) - f(exit|w,m))f(w|m)f(m)w\, dw &\leq \delta \\ \sum_m \int_{w=0}^{\infty} \left(\frac{e^{\frac{w-\mu_m}{T_m}}}{1+e^{\frac{w-\mu_m}{T_m}}} - \frac{1}{1+e^{\frac{w-\mu_m}{T_m}}}\right) f(w|m)f(m)w\, dw &\leq \delta \\ \sum_m \int_{w=0}^{\infty} tanh\left(\frac{w-\mu_m}{2T_m}\right) f(w|m)f(m)w\, dw &\leq \delta \end{aligned} \tag{12}$$

From this rewritten problem, we form the Lagrangian:

$$\begin{aligned} \mathcal{L} = {} & S(f(w|m)f(m)) + \sum_m \int_{w=0}^{\infty} (f(w|m)f(m)S(f(a|w,m)))\ dw \\ & - \sum_m \kappa_m \left(\int_{w=0}^{\infty} f(w|m)\, dw - 1\right) - \sum_m \gamma_m \left(\int_{w=0}^{\infty} f(w|m)w\, dw - \bar{w}_m\right) \\ & - \beta \left(\sum_m \int_{w=0}^{\infty} tanh(\frac{w-\mu_m}{2T_m}) f(w|m)f(m)w\, dw - \delta\right) \end{aligned} \tag{13}$$

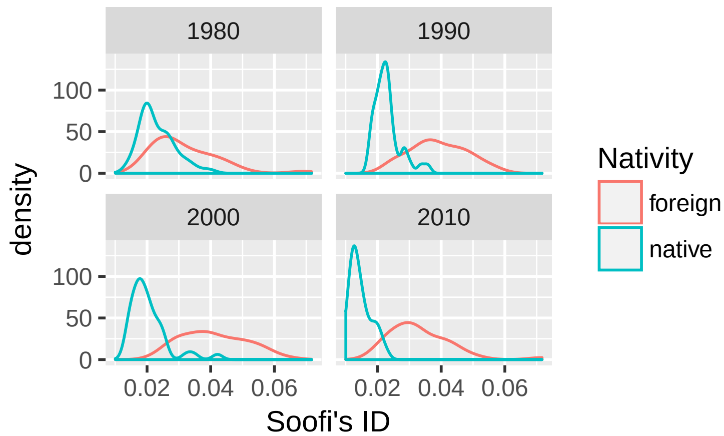

Figure 8: Distribution of Soofi's Informational Distinguishability measures for the fit of the Smithian model to the wage distribiutions by group and metropolitan area.

We calculate the first order condition $\frac{\partial \mathcal{L}}{\partial f(w|m)} = 0$ and solve for $f(w|m)$ using the normalization constraint to obtain Equation 9.

8.2 Data source and construction

For details on the construction of the sample, as well as the wage variable used in this study, refer to Wiener 2018.

Census data comes with a set of administrative and statistical zones which divide up geographic space. It is not clear that labor markets are coextensive with these zones, as happy a coincidence this would be for the researcher. Furthermore, as we begin to study more localized labor markets, the sample sizes shrink. Metropolitan areas provide a compromise between population size and economically meaningful boundaries. The Census Bureau constructs Metropolitan Areas around large population centers by combining counties that have a "high degree of economic and social interaction" (Ruggles et al. 2015). Bridging residential and occupational location in this manner makes it possible to use household surveys to study local labor market structure.

Metropolitan areas change shape over time, and the Census Bureau tries to account for such developments by adding or substracting counties. Public-use microdata also restricts geographic information to varying extent, leading to inconsistencies across years and incomplete identification of metropolitan areas within years (Ruggles et al. 2015).

8.3 Additional Graphs

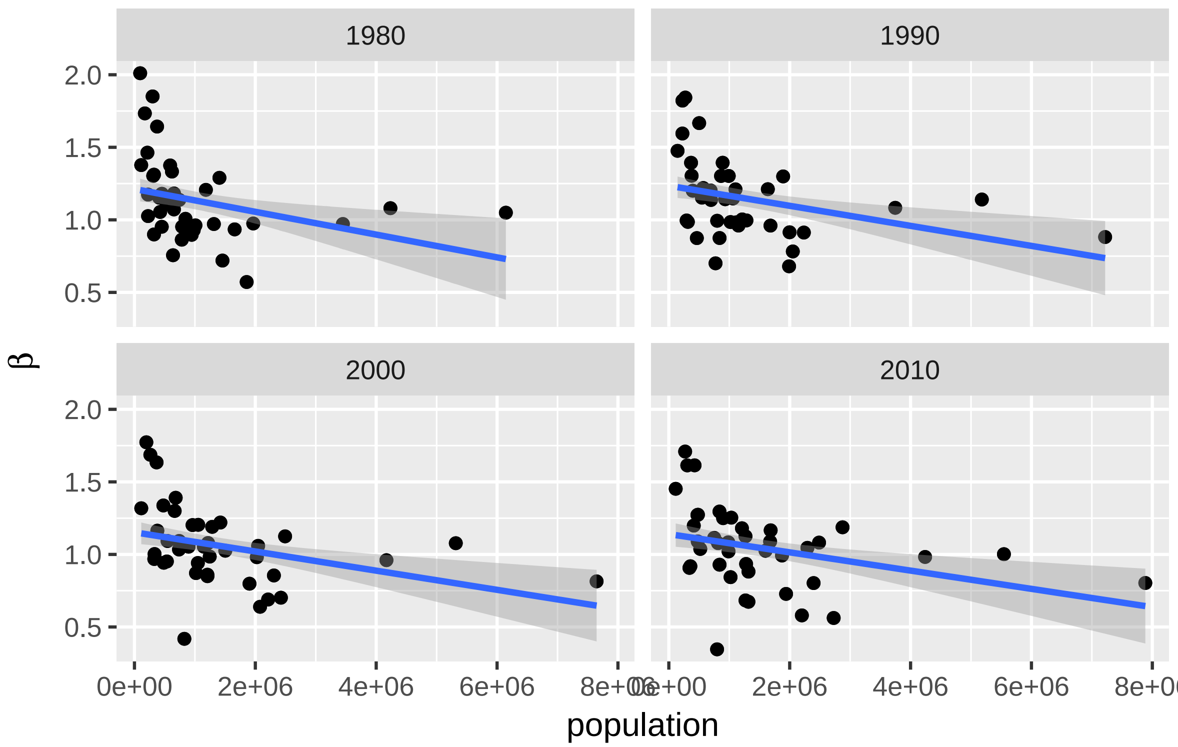

Figure 9: Competitiveness (β) vs. population in major metropolitan areas. 1970-2010 Census and ACS data.

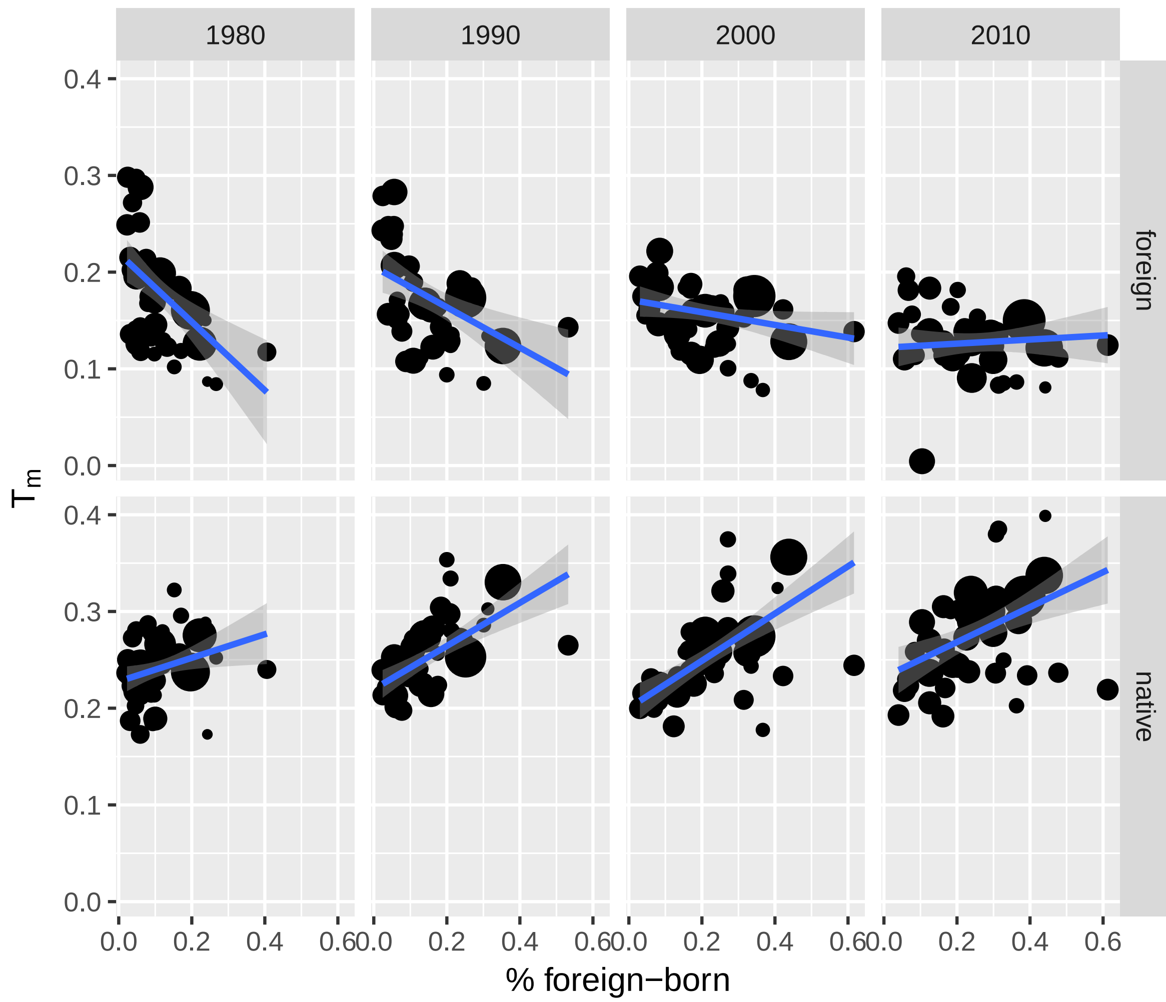

Figure 10: Behavioral temperatures (T_μ) vs. foreign-born share in major metropolitan areas. Size proportional to population. 1970-2010 Census and ACS data.