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The person of the category: the pricing of risk and the politics of classification in insurance and credit

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Abstract
In recent years, scholars in the social sciences and humanities have turned their attention to how the rise of digital technologies is reshaping political life in contemporary society. Here, we analyze this issue by distinguishing between two classification technologies typical of pre-digital and digital eras that differently constitute the relationship between individuals and groups. In *class-based systems,* characteristic of the pre-digital era, one's status as an individual is gained through membership in a group in which salient social identities are shared in common with other group members. In *attribute-based systems*, characteristic of the digital era, one's status as an individual is determined by virtue of possession of a set of attributes that need not be shared with others. We argue that differences between these two types of classification technologies have important implications for how persons attach (or fail to attach) to groups, and therefore what kinds of political mobilization are possible. We illustrate this argument by examining contention over the use of gender as a variable in the pricing of risk in insurance and credit – two markets in which individuals directly encounter class-based and attribute-based systems of classification, respectively.

Keywords Actuarialism · Algorithms · Classification · Credit · Digital politics · Insurance

"Knowledge of the social world and, more precisely, the categories that make it possible, are the stakes, par excellence, of political struggle, the inextricably theoretical and practical struggle for the power to conserve or transform the social world by conserving or transforming the categories through which it is perceived."
– P. Bourdieu (1985: 729)

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Anxieties that the digital era may be transforming the basis of our political life abound in contemporary society. The full contours of this new politics are still emerging, but among its more concerning features are the proliferation of ever more invasive forms of surveillance and social control (Harcourt, 2015; Lauer, 2017; Zuboff, 2019), the presence of new and more subtle forms of discrimination in contexts where decision-making is automated by computers (Benjamin, 2019; Eubanks, 2018; Noble, 2018; Pasquale, 2015), the threat posed to democratic institutions by the manipulation and distortion of information (Bail, 2021; Sunstein, 2017; Tufekci, 2014), and the emerging possibility that the manner in which digital technologies mediate individual subjectivities enervates the very soul of citizenship (O'Neil, 2016; cf. Fourcade, 2021; Isin & Ruppert, 2020). Alongside these various worries, some scholars observe that social media platforms provide new opportunities for collectivities to identify and mobilize adherents, even as these incipient movements may find it difficult to develop the organizational capacities necessary to sustain and deepen campaigns in the digital environment (see Bennett & Segerberg, 2012; Couldry, 2015; Fourcade & Johns, 2020; Milan, 2015; Tufekci, 2017).

Cutting across these varied discussions is the *algorithm*, a mysterious entity endowed with seemingly magical powers to remake the terrain of the social (see Gillespie, 2014). For computer scientists, an algorithm is simply a set of rules that defines a series of steps to solve a problem, converting inputs into an output. Defined in this broad way, of course, algorithms have been around as long as humans have attempted to organize decision-making systematically through the elaboration of rules (Daston, 2022). Additionally, however, algorithms are typically understood as (input-output) decisions made using computers, and hence they are associated with the processing of large quantities of data (i.e., "big data") enabled by the growth of computing power in the latter decades of the twentieth century (see Lauer, 2017). In this narrower sense, the algorithm fully belongs to – and defines – the digital age.

How might the growing salience of algorithms be key to the emerging politics of the digital age? While much of the literature on digital politics has emphasized the opacity of these instruments – "black boxes" that rely on proprietary models to determine access to social services, employment, credit, insurance, housing, and even a potential mate (Eubanks, 2018; O'Neil, 2016; Pasquale, 2015) – our focus here is on how algorithms function as technologies of classification. As the epigraph to this article makes clear, classificatory technologies shape political struggles in part by shaping the possibility of *perception* – what is visible versus what is hidden from view (Fourcade, 2016; cf. Amoore, 2020: 15). But systems of classification are important not only for determining the visibility (or invisibility) of various social objects. Classificatory technologies are also the means by which we are put into relation with others, determining possible lines of connection and fracture (e.g., Bourdieu, 1985; Brubaker, 2005; Elliott, 2021; Fourcade, 2016; Goldberg, 2007; Mora, 2014; Rodríguez-Muñiz, 2021). In this sense, it is classification that makes politics possible, insofar as we understand politics as action in concert (see Arendt, 1998 [1958]).

How, then, do algorithms classify? As Marion Fourcade (2016; 2021) notes, many algorithms classify in an "ordinal" register, producing a *score* that sorts individuals (or whatever object is being classified) into a ranking ordered from *higher* to *lower* rather than, as with many pre-digital forms of classification, by differentiating "nominal" types or kinds.[1] To cite an example that we foreground in our analysis below, in a world governed by algorithms, access to credit is determined by one's credit score – a numerical estimate of the risk of default – rather than by membership in a social category defined by gender, race, or geography (see Fourcade & Healy, 2013a; Hyman, 2011; Krippner, 2017; Poon, 2012).[2] As such, the proliferation of scoring technologies has implications for how groups are constituted around salient social identities (Bourdieu, 1985: 741), and thus for how collective struggles unfold in digital societies.[3]

In this regard, we note that sociological researchers have thought a great deal about how systems of classification (algorithmic and otherwise) establish symbolic boundaries and form group identities, with important consequences for how social inequalities are produced and reproduced (e.g., Bourdieu, 1984; Brubaker, 2015; Fourcade & Healy, 2013a; Lamont et al., 2014; Lamont & Molnar, 2002; Massey, 2007; Ridgeway, 2011; 2019; Tilly, 1998). But they have thought less about how classificatory practices may contribute to the production and reproduction of social inequalities by *obscuring* group boundaries (cf. Monk, 2022).[4] This concern directs us to shift our focus from how classificatory technologies make groups to how these technologies also make *individuals* who either attach or fail to attach to these groups (cf. McFall & Moor, 2018; Moor & Lury, 2018).[5] Accordingly, we suggest that in addition to considering how collectivities are made (and possibly unmade) by new scoring technologies, we also ought to investigate the person who "lives" in the cells defined by our practices of classification. Of course, these concerns are not fully separable, since systems of classification format groups and individuals together (see especially Simon, 1988). Nevertheless, in the following analysis we emphasize the "person of the category," asking how individuals are "summoned" to act, if they are, by classificatory systems that sort, rate, and rank.[6]

In developing our analysis, we are mindful of several difficulties present in the now expansive literature on algorithms (see Beer, 2017; Christin, 2020; Dourish,

1 We are simplifying here since both "nominal" (type or kind) and "ordinal" (score) classifications exist in analog and digital forms (see Fourcade & Johns, 2020: 814). Nevertheless, there is a clear affinity between Fourcade's nominal and ordinal forms of classification and pre-digital and digital technologies, respectively, that we exploit in our analysis below.

2 This is not to suggest that such group memberships no longer matter in the allocation of social goods in societies in which algorithms govern decision-making, but they matter in ways that are not directly visible in the score, as we discuss below.

3 Note that in this article we are translating a broader set of concerns about how the digital is reshaping political life into a somewhat narrower concern with how algorithms – particularly those involving scoring technologies – are changing the potential for political mobilization.

4 We are indebted to Jonah Stuart Brundage for this formulation.

5 It is noteworthy in this regard that Michèle Lamont and Virág Molnar (2002: 188) conclude their expansive survey of the study of social boundaries by calling for "a more elaborate phenomenology of group classification" that would identify "how individuals think of themselves as equivalent and similar to, or compatible with, others."

6 We take our title from Marcel Mauss's (1985) essay on the "category of the person." But rather than examining *the category of the person* in broad anthropological terms, investigating the meaning of personhood in diverse societies and across long spans of time, here we consider *the person of the category* more narrowly by examining how forms of pre-digital and digital classification differently configure the possibilities for personhood – especially as expressed through political mobilization – in contemporary American society.

2016; Rieder, 2017; Seaver, 2017; 2018). One such difficulty is the tendency to discuss "algorithms" in overly broad strokes, referencing generic social processes and glossing over the immense variation in this social form without providing insight into how specific algorithms operate "in the wild" (Seaver, 2017: 2). A second difficulty is to overcorrect for this problem by offering an excessively technical account of specific algorithms that fails to connect to larger understandings of how the digital is reshaping social practices, including political practices (Rieder, 2017). A third problem is one that we are especially sensitive to as historical sociologists: the tendency to overstate the novelty of (apparently) new classificatory systems by underplaying the extent to which algorithmic techniques grew out of and are continuous with prior social logics and practices (Christin, 2020).

Given these various problems, our strategy in this article is broadly comparative and historical, as we believe that we gain the greatest insights by setting the algorithm against other classificatory techniques (cf. Harcourt, 2015: Chapter 5). Accordingly, we neither theorize at the level of "algorithms" generally, nor do we drill down into one specific application. Instead, our goal is to select two broad technologies – represented by the insurance pricing table and the credit score – that we suggest present paradigmatic features of pre-digital and digital forms of classification, respectively. It is important to note that the histories and development of these two technologies are intertwined in complex ways (see Bouk, 2015; Lauer, 2017), invalidating any effort to treat either of these classification systems as fully novel with respect to the other. Nevertheless, we examine these technologies at a historical moment when their critical features were more clearly differentiated from each other than they later became. Accordingly, our approach in the following analysis is broadly Durkheimian, distinguishing earlier and simpler forms from later and more elaborate versions of these technologies so as to identify their essential elements (Durkheim 1995 [1912]). Thus, our contention is that while the advent of "big data," artificial intelligence, and machine learning has changed how algorithms function in contemporary society, the rudimentary scoring systems that preceded (and arguably, prefigured) these developments hold the key to understanding how the rise of scoring technologies has reshaped potentials for collective mobilization in the current era more broadly.[7]

The terminology here is troublesome. It is tempting to refer to the insurance pricing table as an "actuarial" system of classification because this technology depends on sorting individuals into groups defined around broad averages (i.e., following the methods of actuarial science; see Harcourt, 2015: Chapter 5). But some scholars use "actuarial" in a more general sense to refer to any decision technology that relies on predictive statistical methods, displacing more holistic or subjective forms of judgment (e.g., Simon, 1988). It is similarly tempting to refer to the credit score as an "algorithmic" classification technology. But we have already noted that the term "algorithm" can refer broadly to any set of rules that is applied mechanically to produce an outcome or decision. On these broader definitions, both the insurance pricing table and the credit score could

[7] We return to and elaborate on these observations in the conclusion of the article.

be accurately described as "actuarial" or "algorithmic," and indeed it is common in the literature to equate "actuarial" and "algorithmic" techniques as referencing statistical or computational forms of decision-making. But we suggest that the conflation of actuarial and algorithmic classificatory technologies actually hides what is distinctive about politics in the digital era, and we thus need to differentiate clearly between these systems of classification based on how they constitute groups and how individuals are attached to (or detached from) these groups – the key features that define them as *political* technologies, in other words.

Accordingly, in our analysis below, we distinguish between what we refer to as *class-based* (actuarial) and *attribute-based* (algorithmic) systems of classification. In class-based systems, represented here by the insurance pricing table, outcomes are determined by *assigning individuals to membership in a group* in which each person is positioned as "average" or "typical." By contrast, in attribute-based systems, represented here by the credit score, outcomes are determined by *considering an individual's values on a series of variables*. No group membership is constructed; instead, each item in an index is evaluated separately to calculate a total score (Morris, 1966: 54).[8] The critical distinction between these two systems of classification is that in class-based systems each individual is given the *same value* as all other members of the group to which she is assigned, whereas attribute-based systems attempt to give each individual her own *unique value* or score, as closely as this can be approximated (cf. Fourcade, 2016: 189).[9]

Existing research points to a marked shift from class-based to attribute-based systems of classification in recent years (see Espeland & Sauder, 2016; Eubanks, 2018; Fourcade, 2016; Fourcade & Healy, 2013a; Kiviat, 2019; Krippner, 2017; O'Neil, 2016; Pasquale, 2015; Poon, 2012). This is significant because differences between these forms of classification have implications for how individuals connect to groups, and therefore what kinds of political mobilization are possible (or at least likely) in contemporary society. To anticipate, we argue that because the former method of classification attaches individuals to broad (and often highly salient) social categories, it facilitates the formation of the shared subjectivities that are a necessary pre-condition for collective action. In contrast, the latter form of classification detaches individuals from sociologically meaningful groups, making the perception of a shared condition more difficult and attenuating potentials for collective action. We examine these processes in the specific context of political contestation around risk pricing in insurance and credit markets, but we believe that the lessons we draw regarding how different classification technologies affect political

[8] Here is another reason for preferring the language of "attribute-based" over "algorithmic" in describing these systems of classification. The scoring technologies we examine in this article represent only one type of algorithm, albeit an algorithm that is increasingly prevalent and influential in a wide variety of decision-making contexts. But many other computational techniques used to aid decision-making are available (e.g., MacCormick, 2012), and we do not presume that all these techniques operate on group formation in the same way we describe for scoring technologies. Again, our aim in this article is not to theorize the implications of the rise of algorithms in general for the shape of political life, but rather to examine the impact of one particularly important algorithmic technology that intersects a broad domain of critically important social decisions (see O'Neil, 2016).

[9] We might for this reason be tempted to refer to attribute-based systems as "individualized," but this is misleading: these are *both* methods of constituting individuals, albeit with different intuitions about what it is to be a person, as we elaborate below.

mobilization are more broadly applicable, particularly as scoring technologies have spread across social domains in recent years.

In the next section of the article, we elaborate our theoretical argument through an engagement with legal scholar Jonathan Simon's (1987; 1988; Feeley & Simon, 1992) early writings on "actuarialism." Simon's work is prescient in anticipating much of the current debate on algorithms, and yet we suggest that he misreads the dangers that new classification technologies pose to our politics, albeit in ways that allow us to specify these dangers more precisely. In the third section of the article, we explain our case selection and elaborate on the distinctive organizational cultures that have imprinted classification technologies in insurance and credit markets, respectively. In the fourth and fifth sections, we turn to our two empirical cases, examining how distinct classification technologies in insurance and credit markets shape potentials for political mobilization. A concluding section returns to broader considerations about the role of the algorithm in our collective political life, drawing implications from our historical cases in order to delineate the threat posed to political mobilization by the proliferation of new scoring technologies.

Revisiting "actuarialism"

To understand more fully how digital technologies are reshaping the terrain of the political, it is useful to revisit Simon's influential (if somewhat neglected by sociologists) writings on "actuarialism." While Simon (1987; 1988; Feeley & Simon, 1992) developed this work across a number of pieces, the most elaborate statement delineating how actuarial techniques transformed potentials for political action was published in the *Law & Society Review* in 1988, and accordingly we focus our attention here on this article. Written well before digital technologies had fully reshaped the terrain of social life, "The Ideological Effects of Actuarial Practices" nevertheless glimpses into the digital future with a prescient analysis of then newly emerging computational techniques of decision-making that Simon sees as displacing more "qualitative" or "holistic" methods of evaluation. Notably, Simon's discussion of "actuarialism" to refer to the use of statistics to guide decision-making encompasses both what we call "class-based" and "attribute-based" systems of classification: Simon's main case concerns statistical techniques used to price pensions and insurance (corresponding to our "class-based" systems), but he also gives passing attention to scoring technologies used to predict rates of criminal recidivism (corresponding to our "attribute-based" systems). According to Simon (1988: 774), what both of these forms of classification hold in common – and what seemingly defines them as "actuarial" – is the constitution of groups with *no experienced social meaning* for the participants (cf. Harcourt, 2015: Chapter 5). A person classified as a particular risk by an insurance company shares nothing with others so classified other than a series of formal characteristics (e.g., age, gender, marital status, and so on). Even more starkly, a score predicting the likelihood of re-offending may group individuals who hold *only this numerical ranking* in common. In this regard, the actuarial techniques examined by Simon present a marked contrast to older (i.e., pre-actuarial) forms of classification, which also sought to group individuals for purposes of exercising power over them, but did so in ways that created tangible social identities (e.g., "the homosexual," "the multiple personality," "the habitual offender," and so on) (Simon, 1988: 790). As the philosopher Ian Hacking (1986: 229) has noted, by congealing specific ways of being in the world, these categories resulted in "making up" people, expanding the "space of possibilities for personhood" in the process. Notably, these expanded possibilities for personhood potentially enabled resistance by people – i.e., homosexuals, the mentally ill, criminal offenders – summoned into existence by these very categories (Simon, 1988: 791).

Simon argues that no such possibilities for personhood – or resistance – are created by actuarial classifications. The categories used by the insurance company when it groups risks are "singularly sterile," resulting in communities that are inert, immobile, and deactivated (Simon, 1988: 789). But what precisely lies behind this sterility? At the most basic level, Simon notes the "artificiality" of the groups constituted through actuarial practices (cf. Austin, 1983). These are not groups organized around a shared history, common experiences, or active engagement. In this sense, Simon argues that under actuarialism the status groups or classes that grounded classic Weberian and Marxian analyses of social life have been displaced by "aggregates" – alive only in the imagination of the actuary who calculates and tabulates, and not in any lived form of human association. As such, these groupings are exceedingly unlikely to provide the basis of collective mobilization, or any other form of activity we would recognize as "political."[10]

Beyond the constitution of "aggregates," Simon's analysis also gives attention to how such "artificial" groups form persons. As Simon (1988: 786–87; cf. Austin, 1983) notes, the actuary does not "know" us in any holistic sense, but only as a configuration of formal roles that are assembled into a "person." Of course, the notion that we occupy multiple roles in our complex, differentiated society is not in any sense new and can be understood as a core feature of modernity (see Durkheim, 2014 [1893]). But prior to the rise of actuarial techniques, Simon suggests, most individuals were reasonably skilled in managing these multiple roles and weaving them into a coherent self. Particularly important here was the availability of group identities such as race or gender that enabled individuals to integrate other, less salient roles into an overarching narrative of personhood. One consequence of actuarialism, however, is that these group identities have become increasingly "demoralized": they are treated by the actuary simply as efficient ways of differentiating among subgroups in a population and abstracted from any larger history of struggle and domination (Simon, 1988: 780–81; cf. O'Malley, 1996: 194). This demoralization of group identities, Simon argues, has attenuated capacities for self-interpretation in an actuarial society, leaving a set of unconnected fragments. Accordingly, if Hacking (1986) observed how older forms of classification "made people up" by inventing coherent (if often contested) group identities, Simon (1988: 792) provocatively suggests that actuarial classifications may in turn "unmake" persons. This decentered, fragmented subject is a poor candidate for political mobilization.

[10] Simon overlooks the possibility that actuarial classifications might in rare instances constitute *actual* groups founded on common experiences and shared interests. See Nan Hunter's (2008) intriguing exploration of the risk pools organized by group health insurance plans as a potential foundation for democratic deliberation in the workplace.

In this analysis, Simon has usefully identified two mechanisms through which actuarial practices depress political mobilization: first, the formation of groups (or "aggregates") along dimensions that limit the potential for collective identification; and second, the constitution of persons within these groups in ways that fragment subjectivity and disrupt personhood. Notably these mechanisms are fully intertwined in Simon's analysis: it is because aggregates are constructed from "artificial" groups in which *we are not addressed as fully human* that the possibilities for political mobilization are so limited. But once we pull apart the two classificatory technologies that are collapsed in Simon's concept of "actuarialism," it becomes clear that these mechanisms are not only separable but that they operate very differently across the class-based and attribute-based systems of classification that form his empirical examples, with distinct implications for the threat posed to our collective political life.

To take first the problem of group formation, Simon's "aggregates" represent very different entities in the context of the statistical techniques used in pension and insurance pricing from those in score-based predictions of criminal behavior. The first case involves creating groups (or, to use the language of insurers, *classes*) constituted by individuals who share a series of characteristics in common and therefore are presumed to represent the same risk (see Abraham, 1986). As Simon notes, these groups are "artificial" in that they are created by the actuary's calculations rather than lived in practice, but nevertheless a group *is* constituted by these techniques, even if it is a latent one. The second case involves tallying up a given individual's risk factors to arrive at a score that describes the likelihood of re-offending. The only "characteristic" that group members hold in common in this case is the numerical score. As Malcolm Feeley and Jonathan Simon (1992: 466) observe, "In the actuarial criminology of today … the numbers generate the subject itself." Accordingly, we may wonder whether there is a "group" here at all, particularly since the aim of scoring technologies is to give each individual her own *unique* score. Thus, if a group exists, it is incidental to this classification technique, not (as in the first example) constitutive of it.

When we turn from the formation of groups to the fragmentation of subjects within these groups, it is similarly evident that the implications of Simon's analysis for political mobilization vary depending on what *kind* of classification we are considering, class-based or attribute-based. In the case of insurance pricing, Simon's (1988: 793–94) concern that actuarial techniques reduce individuals to a series of formal roles that do not have any "moral density" and hence do not "grant an identity" that organizes a coherent sense of self seems broadly valid. But the extent to which actuarial techniques have actually *succeeded* in neutralizing group identities needs to be carefully qualified. Indeed, we suggest below that the inscription of nominally "demoralized" categories such as gender into class-based systems of pricing makes their full demoralization difficult to achieve – and itself a stake in struggle. In the case of scoring technologies, the fragmentation of subjects that Simon describes seems more fully realized, but notably the score does not appear to achieve this affect via the demoralization of group identities, as he suggests.[11]

[11] On the contrary, Fourcade (2016: 187) suggests that scoring technologies are a primary vector by which group identities are reinscribed as *moral* differences: "Since credit scores are 'blind' to categorical differences in their design, any categorical difference in credit behavior that surfaces *appears* to be rooted in the relative 'merit' (or moral 'nature') not simply of individuals but of categorically different populations, *as if* one could identify some essential, moral difference between them."

Rather, as Antoinette Rouvroy and Thomas Berns (2013: xi) aptly observe, scoring technologies continually swap out predictors, "shuffling the cards" such that there is no stable basis for constructing group memberships – or a coherent sense of self on the basis of these memberships (cf. Cheney-Lippold, 2017).

To summarize this discussion and preview our own argument, we suggest that the groups (or aggregates) contained in the cells of the insurance pricing table may be artificial, but these are still *potential* collectivities that can under particular circumstances be activated. This potentiality, we argue, reflects the fact that insurers assign individuals to membership in groups (however "thinly" conceived) based on characteristics held in common, leaving open the possibility for the construction of shared subjectivities and action in concert. In contrast, the credit score does not attach individuals to groups (or aggregates), but rather positions each individual according to her possession of a series of attributes tallied to produce a score. To the extent that there is a "group" here, it is formed by the score itself and does not reflect any characteristics shared among group members. In any case, these characteristics are frequently updated in scoring models, destabilizing any basis for common affiliation. Hence, individuals are detached from sociologically meaningful groups, thereby diminishing possibilities for political action.

The site for our investigation is the pricing of risk in insurance and credit – two markets critical for life chances in which individuals directly encounter class-based and attribute-based forms of classification, respectively. In the following analysis, we examine systems of classification used in the pricing of insurance and credit during a period in the 1970s and 1980s in which risk classification was politicized by social movements seeking to end gender discrimination in these markets (see Austin, 1983; Heen, 2014; Horan, 2021; Hyman, 2011; Krippner, 2017, 2021; Simon, 1988; Thurston, 2018; Trumbull, 2014). The divergent histories of contestation over the use of gender as a pricing variable in insurance and credit markets provide an illuminating vantage point on how these systems of classification differently organize (or disorganize) political mobilization. The class-based systems used to price risk in insurance markets grouped individuals on the basis of gender (and other salient characteristics such as age and marital status), treating individuals as "average" members of the risk classes to which they were assigned. Insurers' class-based pricing techniques provided a ready target for feminists mobilizing against discriminatory practices, as well as ample opportunity for the formation of shared subjectivities that were the necessary precondition for such mobilization. By contrast, lenders' adoption of credit scoring techniques did not involve placing individuals into groups, but instead treated each individual "as an agglomeration of attributes … probabilistically associated with a repayment outcome" (Marron, 2009: 127). As such, credit scoring disorganized feminist opposition to discriminatory practices in credit markets by effectively dislodging the individual from membership in groups defined by gender (or on any other basis), undercutting awareness of a shared positionality and therefore capacity for political mobilization.

In our analysis, we focus on how class-based and attribute-based forms of pricing differently constitute the individual for purposes of political mobilization by attaching personhood to (or detaching personhood from) membership in groups. As an empirical matter, this aspect of our analysis is closely intertwined with another element, which is the degree to which social categories such as gender are salient or suppressed in these classification systems. Notably, there is an affinity – demonstrated in our empirical cases – between class-based systems that assign personhood based on group membership and the incorporation of recognizable social categories into statistical frameworks. There is equally an affinity between attribute-based systems that de-emphasize group membership and the suppression of socially significant categories. As we make clear in our empirical analysis, capacities for political mobilization are jointly determined by how individuals are constituted as members of groups *and* whether these groups are organized by sociologically meaningful categories or not. Notwithstanding these affinities, however, we think that these two aspects of our analysis are analytically separable from one another. That is, if insurance risk classes were formed around sociologically meaningless collectivities, *class-based pricing systems would still make possible the identification of fellow class members*, and therefore create the potential for the formation of new collective political actors.[12] Conversely, if credit scoring models incorporated sociologically meaningful categories, *attribute-based systems would still impede possibilities for collective action by detaching individuals from groups*.[13]

One final prefatory note is in order: we compare these pricing systems at a historical moment in which differences between them were more starkly defined than they are at present when credit scoring techniques have increasingly moved into insurance pricing (see Kiviat, 2019; Rona-Tas, 2017). Similarly, we also place our study at a point in time when scoring technologies were first emerging and their development was still quite rudimentary. This is actually advantageous for our argument because it allows us to discern the essential features of these systems more easily than we could by examining later iterations of these technologies. Thus, the fact that we are examining purer and simpler versions of technologies that later become more mixed in form and more elaborate in structure provides particular clarity on a moment of transition (cf. Durkheim, 1995 [1912]).

Two classification technologies

We think of our "cases" as the two classification technologies at the center of our analysis since our goal is to understand how each of these technologies organizes (or disorganizes) political contention. In this regard, we treat these systems of classification – and the forms of political engagement they generate – as representative of broader developments occurring outside the particular domain of credit and insurance. Thus, the insurance pricing table and the credit scorecard can be viewed as cultural artifacts of a sort, congealing and expressing social relationships in a way

[12] We provide some evidence for this below by examining the National Organization for Women's efforts to organize opposition to insurance pricing by mobilizing "low-mileage" drivers as the constituency harmed by insurers' classification practices.

[13] We are indebted to conversations with Nathan Wilmers and Sasha Killewald for the discussion in this paragraph.

that is especially useful for exploring the nexus of classificatory systems, the exercise of political power, and emergent forms of personhood in contemporary society. These technologies do not exist in a vacuum, however. Accordingly, our task in this section is to situate the insurance pricing table and credit score in the broader social context in which they developed. We do so here through a discussion of distinct, although intertwined, organizational cultures of the insurance and credit industries.

Both insurance and credit are industries in which profitability is dependent on successfully predicting contingent events in the future – in the case of insurance, actuaries estimate the risk of mortality, illness, or accident; in the case of credit, loan officers estimate the risk of default. In both cases, risks must be estimated based on data aggregated from the experiences of others. Despite this similarity, insurers and creditors go about inferring estimates of individual risk based on aggregated data quite differently – differences that reflect the distinct histories (and, even more fundamentally, social ontologies) of the two industries. These differences are significant for how classification practices in both industries shape possibilities for collective action, as our analysis demonstrates.

Organizational cultures in insurance

The precursors of modern insurance are rooted in the guild institutions of medieval Europe and, somewhat later, industrializing England's expansive network of mutual aid societies. Like modern insurance organizations, these institutions collected contributions from their working-class members to provide modest support in the event of the illness or death of a household head (see Gosden, 1961; Hopkins, 1995; Stalson, 1942; Zelizer, 1979). The key distinction between modern insurance and its premodern predecessors reflects the extent to which these various institutions engaged in some form of *risk classification*. Notably, early mutual organizations did not recognize *any* differences among members of the risk pool, with all individuals assessed equal contributions even if they might represent substantially different risks to the community (Alborn, 2009; Clark, 1999). By contrast, the defining feature of modern insurance is its reliance on segmenting the risk pool into distinct classes, each assessed a price consistent with the particular risk individuals assigned to that class are assumed to represent (as closely as this can be estimated by actuaries) (Gowri, 1997; Stone, 1993).

Risk sharing and risk segmentation are in fact flip sides of the same coin, and both reflect the way insurance creates a web of interdependencies among participants in a risk pool rather than a purely dyadic tie between insurer and insured (Baker, 2002: 36; Lehtonen & Liukko, 2011: 41; Stone, 2002: 55). The insurance risk pool establishes a common fund that will cover anticipated losses; because all contribute to this fund, if a given person pays *less* than her fair share (determined by the risk she contributes to the pool), another person must pay *more* (Gerber, 1975: 1207; Lautzenheiser, 1976: 8; cf. Josephson, 1960). In this context, insurers define fairness as involving the construction of *homogenous* risk classes – i.e., classes in which individuals with similar levels of risk are grouped together such that lower risk individuals are not in the position of inadvertently "subsidizing" higher risk individuals (Abraham, 1986). Accordingly, the objective of risk classification is to identify specific characteristics believed to determine an individual's propensity to experience an adverse event, forming groups within which risk is (approximately) equally shared. Of course, the problem is that the characteristics associated with risks of various kinds are nearly infinite; since they cannot all be identified and priced in each risk classification scheme, there will necessarily be unpriced sources of heterogeneity among individuals in any given risk class (Wortham, 1985). Thus, subsidies are inevitable, although how and when they become visible is subject to political contestation, as we show below.

The result of insurers' focus on risk classification is that the notion of the *class* is built into the pricing practices (and social imaginary) of actuaries (see Barry, 2020; Barry & Charpentier, 2020; Ewald, 2020; Krippner, 2021). According to one commentary, "[M]ost actuaries cannot think of individuals except as members of groups" (Brilmayer et al., 1980: 508). Below we observe insurers' tendency to treat individuals-in-classes as *whole persons*.[14] By this, we simply mean that the constituent unit of the class is the *person* (i.e., an individual characterized by age, sex, marital status, and driving record, among other salient features) rather than the *variable* (e.g., age, sex, marital status, and driving record) dislodged from the person. Practically speaking, the fact that insurers imagine classes constituted by whole persons means that data are *cross-classified* (Weisberg & Tomberlin, 1982): rather than analyze data on each variable of interest, insurers identify a *group of individuals* who share relevant characteristics in common and observe loss experiences for this group. This feature of actuarial practice significantly constrains insurers precisely because *there are many fewer individuals who hold a set of characteristics in common* than there are observations on each such characteristic (or variable) considered independently. Accordingly, the classifications selected by insurers to price risk tend to be relatively "sticky": it is more difficult to reconfigure a pricing scheme organized around classes than it is to swap out variables one-by-one (Casey et al., 1976: 108).[15]

[14] When we refer to "whole persons" here and below, we do not mean that insurers treat persons holistically in some broader sense; in this regard we are in agreement with Austin (1983) and Simon (1988) that insurers "know" individuals primarily through their formal roles.

[15] The key issue here seems to be the number of observations needed to generate reliable estimates of loss. Insurers' reliance on cross-classified data may result in a small number of observations *per cell,* even when insurance databases are large (Chang & Fairley, 1978: 27). This means that insurers will be reluctant to discard variables on which they have accumulated observations, favoring variables already in use in a classification system (see Abraham, 1986: 78–9; Casey et al., 1976: 108). In addition to such technical constraints, insurers' use of class-based methodologies imposes what we might consider cultural limits on the selection of pricing variables, as well. Risk plans must be socially acceptable: individuals who purchase insurance are typically very sensitive to being grouped with others who are "like" them as a basic indication of fairness (Ferriera et al., 1978: 131). Since these sensitivities are shared by state regulators who must approve risk classification schemes, insurers are not able to substitute variables freely in response to efficiency, cost, or other considerations. Creditors are considerably less constrained with regard to both technical and cultural aspects of pricing systems, as we discuss below (see footnote 46).

Organizational cultures in credit

The credit industry initially drew inspiration from the precision of actuarial science, and creditors' attempts to adopt more systematic methods of decision-making directly emulated insurance practices (Lauer, 2017). As David Durand (1941) – widely credited with developing the statistical work that laid the groundwork for modern credit scoring – wrote in his thesis, "The actuarial analysis of risk along the lines used in insurance is the goal toward which credit research should strive" (cited in Lauer, 2017: 202). Similarly, early adopters of "pointing systems," such as the Chicago-based mail order company Spiegel's, were explicit about modeling their practices on those utilized in pricing insurance. As Henry Wells (1963: 6), Spiegel's Credit Manager, observed, "The pointing system is built on actuarial principles. It creates experience tables for all groups, types, and cross-classifications of credit customers." Wells went on to note that just as insurers did not attempt to predict outcomes for any given individual, creditors too hewed to group averages in their attempt to price the risk of default.

However noteworthy these similarities between credit and insurance, the two industries were marked by deeper divergences – divergences that became more significant as the practice of credit scoring developed. Credit scoring in its modern form was invented by William Fair and Earl Isaac, two business consultants who in the 1950s began to apply Durand's statistical investigations to the commercial enterprise of pricing risk (Poon, 2007, 2012). Fair and Isaac hailed from the field of operations research, a point of origin distinct from actuarial science (see Harcourt, 2015: Chapter 5). Operations research evolved as a science of decision-making first applied to military operations and later extended as a branch of management in the postwar period by researchers located at RAND and MIT (Thomas, 2015). The signature of operations research was its pragmatic approach to problem solving, with an emphasis on cost reduction rather than theoretical precision or meticulous research. Just as theaters of war required rough and ready tactical solutions, the basic intuition of operations research was that a variety of quantitative techniques – linear programming, game theory, and other optimization methods – could be as profitably applied to business as they were to war (Thomas, 2013). The ultimate goal of operations research was to flexibly take advantage of whatever data could be assembled to "allow better decisions to be made more often" (Thomas, 2015: 98).

One result of this orientation was that creditors were not especially encumbered by notions of fairness, or any other larger considerations that impinged on insurers. Most notably, in stark contrast to actuaries' attachment to the notion of the *class* – an attachment that constrained the choice of analytical technique (see Lengwiler, 2009) – creditors embraced whatever technique seemed to yield reasonable predictions of default at a relatively low cost. As credit scoring developed, this directed creditors toward the use of discriminant analysis – a variation on multivariate regression – to mine loan applications for variables that predicted the risk of default

(Lewis, 1994).[16] Risk was investigated not within classes of "identical" individuals, but variable by variable, as creditors aggregated data across applicants in a manner consistent with multivariate statistical techniques (Morris, 1966: 54). This flexibility ultimately made it considerably easier for creditors to substitute proxy variables into scoring models when feminists challenged the use of sex and marital status in credit decisions (see Casey et al., 1976: 108; Krippner, 2017).

These differences in orientation between class-based insurance pricing and attribute-based credit scoring correspond to differences in each industry's mode of individuation and, in turn, to differences in processes of contestation. In the following sections, we show how class-based insurance pricing was contestable in terms of legible social categories, reinforcing the salience of existing categories and generating novel ones. In contrast, attribute-based credit scoring proved much less productive of mobilizable social groups and thus created challenges for its critics.

We should forewarn our reader that here we examine our two cases out of strict chronological order, since feminist mobilization in credit markets preceded mobilization over insurance pricing by a full decade. The ordering of our cases reflects the historical evolution of these pricing technologies – credit scoring being a much more recent development than risk classification in insurance – rather than the timing of social movements organized around them.

Class-based pricing in insurance

Insurers are in the business of classification. The basic profitability of the industry depends on correctly grouping risks (Abraham, 1986), as a perusal of any insurance textbook will quickly reveal. In an even more fundamental sense, the very identity of the actuary rests on the "the study of the class" (Root, 1915 cited in Rothstein, 2003: 73), and as such it is not surprising that the practices of actuaries are oriented around a few standardized, and in some cases highly elaborate, classification systems. The following classification scheme for pricing auto insurance – the basic elements of which will be familiar to anyone who has purchased insurance for a vehicle – was created by the Insurance Services Office in 1976 and is still (with minor modifications)

[16] Notably, multivariate statistical techniques were adopted much earlier in credit than in insurance. Durand's (1941) early research relied on discriminant analysis, and as the practice of credit scoring developed this method of analysis continued to be used, supplemented by other techniques such as linear regression, logistic regression, and decision trees (Hand & Henley, 1997: 524). In insurance, by contrast, multivariate techniques were slow to develop, and were still considered experimental (and even treated as suspect by many insurers) as late as the 1970s and 1980s (see Cummins et al. (1983) for life insurance; see Casey et al. (1976); Massachusetts Division of Insurance (1978); and New Jersey Department of Insurance (1981) for auto insurance). When actuaries did finally adopt multivariate statistical techniques, they were used not to score discrete variables (or risk factors) that could then be tallied to arrive at an individualized price (as in credit scoring), but simply to produce more reliable estimates of cell-means calculated by observing *the average loss experience of members of a given risk class* (e.g., Hsiao et al., 1990). In other words, modern multivariate statistics were made to conform to the requirements of class-based pricing rather than disrupting this system (see Barry, 2020).

YOUTHFUL OPERATOR
Not eligible for Good Student Credit

AGE			UNMARRIED FEMALE		MARRIED MALE	
			Pleasure Use or Farm Use	Drive to Work or Business Use	Pleasure Use or Farm Use	Drive to Work or Business Use
WITHOUT DRIVER TRAINING	17 or Less	Factor	1.75	2.00	1.95	2.20
		Code	8211— —	8212— —	8311— —	8312— —
	18	Factor	1.60	1.85	1.85	2.10
		Code	8221— —	8222— —	8321— —	8322— —
	19	Factor	1.50	1.75	1.75	2.00
		Code	8231— —	8232— —	8331— —	8332— —
	20	Factor	1.25	1.50	1.65	1.90
		Code	8241— —	8242— —	8341— —	8342— —
WITH DRIVER TRAINING	17 or Less	Factor	1.60	1.85	1.70	1.95
		Code	8261— —	8262— —	8361— —	8362— —
	18	Factor	1.50	1.75	1.65	1.90
		Code	8271— —	8272— —	8371— —	8372— —
	19	Factor	1.40	1.65	1.60	1.85
		Code	8281— —	8282— —	8381— —	8382— —
	20	Factor	1.20	1.45	1.55	1.80
		Code	8291— —	8292— —	8391— —	8392— —

Fig. 1 Class-Based Pricing (Insurance Pricing Table). Source: Government Accounting Office (1979)

widely used in the industry today (see Fig. 1). We have reproduced here only a fragment of a larger classification system that contains some 161 cells, but this selection captures the essential features of this system.

Consider one cell in this table: the uppermost, left-hand cell "contains" unmarried female drivers, aged 17 or younger, who have not received driver training, and who use a car for pleasure or on a farm. To assign drivers with these characteristics a price for auto insurance, the insurer collects data on the accident history of drivers with precisely these characteristics and estimates likely claims based on this prior experience (see Zoffer, 1959). The cost of covering these projected losses is then allocated across all policyholders who share these characteristics in order to determine the premium paid by each individual.[17] Of course, the insurer cannot predict which *particular* individuals in this group will have accidents, but knowing the experience of particular individuals does not matter from the perspective of the insurer. What does matter is having a large enough group in each risk class so that the insurer can accurately predict that *some number* of individuals will have accidents over a given period of time. In this regard, as historian Jonathan Levy (2012: 204) notes, "the law of averages" is the basic rule in insurance markets.

[17] We have simplified auto insurance pricing here for ease of presentation. In addition to classifying individuals by driver characteristics, insurers also classify vehicles by the territory in which they are garaged. Each of these two sets of classifications produces a "relativity" – indicating how much greater or lower the propensity to file claims is for drivers with a particular set of characteristics or a car garaged in a particular territory compared to the statewide average. Thus, classification by driver characteristic and by territory produces two different sets of prices, and the key controversy roiling the insurance industry beginning in the mid-1970s (as auto insurance rates quickly inflated) was how to combine them to calculate a fair premium (see Casey et al., 1976; Florida Department of Insurance, 1979; Government Accounting Office, 1979; Massachusetts Division of Insurance, 1978; New Jersey Department of Insurance, 1981).

As we have already discussed, systems of pricing such as those used in auto insurance can be described as "class-based." Broadly speaking, insurance pricing relies on statistical techniques concerned with determining an average value (or expectation of loss) in order to construct "classes" that are imagined to be internally homogeneous (Abraham, 1986). In this sense, the insurance table reflects a mode of statistical knowledge that is oriented toward a social world made up of groups and aggregates – groups and aggregates that these same techniques help to constitute and to govern (Bouk, 2015; Hacking, 1990; Witt, 2004). Notably, the insurance table also embeds a particular social ontology with regard to individuals, who are treated as *typical* or *average* members of the group or class to which they are assigned (New Jersey Department of Insurance, 1981: 69; Stone, 1978: 153).

Class-based systems of decision-making are so deeply woven into the fabric of our social institutions that we take them almost for granted, but consider as key examples the practice of marketing researchers when they target a product toward a particular demographic group, or the practice of pollsters when they determine the appeal of a political candidate to voters in a particular region or religious group.[18] In these instances, individuals are addressed as members of categories, often delineated through the implementation of surveys, which is perhaps the key technology in the construction of "statistical citizens," as historian Sarah Igo (2007) has argued.

Of course, the manner in which actuarial techniques constitute classes not only facilitates the management and control of these groups, but also enables resistance. Here it is critically important that insurance pricing techniques treat the individuals who "occupy" classes – in this case, our unmarried 17-year-old female without driver training – as *whole persons*. That is, individuals, not separate attributes, are priced in this system: to occupy this cell (and receive the specified price), I must be unmarried, female, 17 or younger, without driver training, and with the appropriate car usage – all of these characteristics *together* place me in this particular category, along with others who share these same characteristics. In this regard, to borrow Carol Heimer's (1985) evocative phrase, the insurance risk class joins together similarly situated individuals in a "community of fate."

To be sure, these are "communities" created by the operations of statisticians and in this sense quite different from the lived communities of workers, neighbors, and co-religionists that characterized the traditional mutual organizations displaced by modern forms of insurance (Clark, 1999; Gosden, 1961; Levy, 2012; Zelizer, 1979). Accordingly, there is no actual group corresponding to the cell comprising unmarried adolescent girls without driver training who collectively mobilize to resist their treatment by insurance companies. As we have already observed, this is the sense in which Simon (1988; cf. Austin, 1983) treats the actuarial techniques that underpin insurance pricing as inherently depoliticizing: these techniques place individuals in groups that have no lived social meaning. There is a great deal of validity in Simon's analysis, but also an important irony, as the very case that Simon relies on to illustrate his argument – the use of gender classifications in pension and insurance

[18] Roi Livne (2021: 921-22) identifies a particularly striking example of class-based decision-making: the practice of using demographic categories such as age, education, gender, race, and ethnicity to ascertain the wishes of dying individuals when they are unable to communicate these wishes directly (because currently incapacitated and having failed to document their preferences when in a condition to do so).

pricing – has in fact been the site of sustained political contestation over several decades (e.g., Austin, 1983; Heen, 2014; Horan, 2021; Krippner, 2021). How should we make sense of the fact that this supposedly depoliticizing technology has generated such a vigorous politics (cf. O'Malley 1996: 194)?

Here we think it is significant that while a given cell in the insurance pricing table may not correspond to any actual social grouping, each risk class is nevertheless constructed from social categories that organize and structure individual experience in our society more broadly (Austin, 1983; cf. Stone, 1993: 314). In other words, these categories (e.g., age, marital status, and gender) are rooted in a set of shared material conditions and institutionalized social practices. Accordingly, the statistical "communities" formed by practices of risk classification may be artificial, but their construction is not arbitrary. Again, this reflects the fact that the pricing of insurance involves the creation of *classes* rather than the evaluation of a series of independent attributes. In constructing classes, insurers imagine whole persons who share socially significant characteristics in common, and those classified by insurers understand themselves similarly (even as the resulting "classes" may spill over the boundaries of particular cells).[19] As a result, social difference remains legible in this system (i.e., "men" and "women" perceive themselves as members of distinct classes), and provides a basis for ongoing struggle around the social meaning and deployment of these categories (cf. Moor & Lury, 2018).

NOW's insurance campaign

This is in fact what the history of political contestation around the use of gender classifications in insurance markets demonstrates: the class-based nature of insurance pricing has resulted in gender remaining salient to regulators and activists alike despite efforts – eventually successful in the case examined here, if not in the industry more broadly (see Heen, 2014) – to eliminate gender classifications from insurance markets. In 1982, the National Organization for Women (NOW) launched its "Insurance Project," a major campaign aimed at ending gender discrimination in the insurance industry (Krippner, 2021).[20] At the time NOW initiated this campaign, men and women could expect to pay significantly different prices for access to coverage across most lines of insurance in the United States. While a patchwork of state laws regulated insurers' rating practices (see Avraham et al., 2014), there was no federal law that regulated insurance pricing in *any* line of business, even though similar bans pertaining to gender discrimination in employment, housing, and credit had been on the books since the 1960s and 1970s.[21] Thus, insurance appears to have

[19] Put differently, the cell is not itself the unit at which mobilization occurs (as Simon (1988) correctly observes) but is constructed from socially legible characteristics that enable mobilization across cells.

[20] "NOW Insurance Project," October 29, 1982, MC 623, Folder 5, Box 126, National Organization for Women Legal Defense and Education Fund Records, Schlesinger Library, Radcliffe Institute, Harvard University, Cambridge, MA.

[21] This continued to be the case until the passage of the Affordable Care Act in 2010, which prohibited the use of gender in determining the price of health insurance. The European Union passed comprehensive legislation banning the use of gender as a pricing variable across all lines of insurance in 2012 (Mabbett, 2014), making the case we examine here anomalous not only with respect to other institutional domains in the United States, but also with respect to insurance practices in the international context.

been left behind by the civil rights revolution that has transformed how Americans exchange goods and services in the marketplace (Graham, 1990).

Auto insurance was an early, if perhaps unlikely, target of NOW's activities in the insurance area.[22] Auto insurers relied on a two-tier pricing structure in which young women paid lower premiums for insurance than young men, but older drivers were priced according to a unisex system in which men and women paid equivalent premiums for insurance coverage. This convoluted pricing structure complicated NOW's campaign since the fact that young women paid lower premiums compared to young men created the appearance that women *as a whole* benefited from gender-based pricing. But rather than demand that insurers extend lower (gender-based) premiums to older women drivers, NOW wanted insurers to desist from using gender as a pricing variable altogether. "We don't want the [insurance] industry to discriminate better, [but not] to discriminate at all," NOW proclaimed.[23] NOW insisted that even in cases where insurers' pricing practices appeared to advantage women, the use of gender classifications was damaging to women's equality, reinforcing stereotypes about gender difference that NOW sought to overcome.[24]

Of course, feminist activists were keenly aware that such arguments in favor of "abstract equality" could be easily turned against them.[25] The large insurance company Aetna was particularly aggressive in doing precisely this, creating a widely circulated advertisement with the provocative heading "Our Case for Sex Discrimination."[26] The advertisement featured an image of a man and a woman each sitting atop a taller and shorter stack of smashed cars, with accompanying text explaining that in a unisex pricing system women would necessarily absorb the cost of men's higher accident risk. NOW knew this claim to be disingenuous, since gender-based pricing only applied to younger drivers and in fact the vast majority of drivers were assessed unisex prices.[27] But these were subtleties that were difficult to convey to the general public, no matter how carefully NOW attempted to hone its messaging. Accordingly, feminist activists feared that the "hoax of beneficial discrimination" would do damage to the larger struggle for the Equal Rights Amendment (ERA), a campaign that was seen as integrally connected to the insurance fight.[28]

[22] NOW also targeted gender discrimination in health, disability, and life insurance (see Krippner, 2021).

[23] "Sex Bias Alleged in NOW Suit," *Philadelphia Inquirer*, August 17, 1984.

[24] Interview with Deborah Ellis conducted by Greta Krippner, February 8, 2017, Rutgers, New Jersey.

[25] "Memo to Preparers of PA NOW Insurance Case from Twiss and Pat Butler," September 14, 1986, MC 666, Folder 4, Box 363, NOW LDEF Records.

[26] "Aetna: Our Case for Sex Discrimination," MC 496, Folder 26, Box 117, National Organization for Women Records, Schlesinger Library, Radcliffe Institute, Harvard University, Cambridge, MA.

[27] In fact, NOW believed that insurers adopted gender-based pricing for younger drivers precisely so that they could (falsely) claim that *all* women got a break on their auto insurance premiums, hence concealing the overcharge paid by women drivers over the age of 25 (see Butler et al., 1988). "Complaint: Pennsylvania NOW versus State Farm," September 23, 1986, MC 666, Folder 4, Box 363, NOW Records; "Plaintiffs' Brief in Opposition to Defendants' and Insurance Department's Motions for Stay of Proceedings, More Specific Pleadings, and Dismissal of Plaintiffs' Claims," November 21, 1986, MC 666, Folder 1, Box 132, NOW Records; "Brief for Petitioners Requesting Review of Insurance Commissioners' Opinion and Order," September 14, 1987, MC 496, Folder 25, Box 117, NOW Records.

[28] "Memo to NOW National Board from Sheri O'Dell Re: Insurance Discrimination Activity," May 1, 1986, MC 666, Folder 4, Box 363, NOW LDEF Records; "Memo to Preparers of PA NOW Insurance Case from Twiss and Pat Butler," September 14, 1986, MC 666, Folder 4, Box 363, NOW LDEF Records.

Under these circumstances, NOW attempted to reorient the discussion from abstract principles of equality to a more concrete analysis of benefits and harms imposed by different pricing schemes. Ironically, this involved meeting insurers on their own terrain, with the fairness of any risk classification scheme determined by how closely it aligned an individual's cost to her level of risk. As we noted earlier, the main conceit of insurance pricing is that each risk class is internally homogenous, grouping individuals who share the same probability of loss (and therefore should pay the same price for insurance coverage). But of course, identifying groups in which all individuals actually represent the same risk (or cost) is close to impossible: in any group, however constructed, some individuals will be higher than the average risk, and others lower (Stone, 1978: 153). In this regard, insurers' claim to have sorted individuals correctly into risk classes amounts to the assertion that there is no *feasibly identifiable* subset of individuals with a higher or lower risk than average for the class (New Jersey Department of Insurance, 1981: 70); in other words, the distribution of risk should be essentially random within risk classes. Feminists challenged the pricing practices of State Farm precisely on these grounds, asserting that there was in fact *systematic* variation within risk classes defined by gender that had not been priced.[29]

But what was this unpriced element? Rather than assuming that some quality intrinsic to men and women produced their different rate of accidents, NOW argued that gender was merely a proxy for the true, underlying "cause" of accident risk: *time on the road*.[30] To support its case, NOW marshaled extensive statistical data showing that, at every age, women drove significantly fewer miles than men and therefore had lower exposure to accidents.[31] "It happens to be [the case] that men drive every year twice as many miles as women," NOW's Twiss Butler explained to the host of Philadelphia radio call-in show. "Now that doesn't mean that all men drive twice as many miles as women. But it means that if you want to look at people as sex-classes, *which is certainly not the way NOW wants to look at them*, that's the ratio you get."[32]

Accordingly, when in 1986 Pennsylvania NOW filed a lawsuit against State Farm and three other auto insurance companies operating in the state of Pennsylvania,[33] the organization demanded that insurance regulators prohibit the use of gender

[29] "Plaintiffs' Hearing Brief," August 14, 1987, MC 496, Folder 24, Box 117, NOW Records.

[30] Paradoxically, when sex was first introduced as a rating variable in the 1950s, insurers seemed to share this understanding. As one history of automobile insurance rating notes, "[T]he first attempt to recognize a statistical difference between young male and female drivers … was not based on the belief that female drivers were necessarily better drivers than male drivers of a comparable age, but rather that the *exposure was less* with young female drivers because of their infrequent use of a family car as compared with that of a young male driver" (Zoffer, 1959: 158; emphasis added).

[31] "Plaintiffs' Hearing Brief," August 14, 1987, MC 496, Folder 24, Box 117, NOW Records.

[32] "Dialogue on Pennsylvania NOW's Auto Insurance Sex Discrimination Lawsuit," September 23, 1988, MC 496, Folder 23, Box 117, NOW Records; emphasis added.

[33] Other insurance companies named as defendants in the lawsuit were Nationwide, Allstate, and Liberty Mutual Insurance. In addition, the Insurance Services Office, the state agency that pools data to create standardized risk classifications for use by smaller insurers, was also included in the complaint.

classifications *and* also require the use of mileage data to set premiums.[34] More specifically, NOW's lawsuit sought an injunction blocking the implementation of a *prior* legal ruling that would have prohibited sex-based prices in insurance until regulators also imposed mileage as a rating factor. NOW argued that only this two-pronged remedy would avoid the inadvertent subsidization of high-mileage (i.e., predominantly male) drivers by lower-mileage (i.e., predominantly female) drivers that would result under full unisex pricing.[35] This approach was controversial, stunning some of NOW's staunchest allies, including the American Civil Liberties Union and the League of Women Voters (both parties to the sex discrimination suit whose implementation NOW was seeking to block).[36] But from NOW's perspective, requiring that insurers rate on mileage was the only way to have truly "sex-neutral" (as opposed to "false unisex") pricing: a pricing system that did not require women to pay for men's higher risk of accident.[37]

Achieving "sex-neutral" pricing required a novel legal theory: rather than discrimination against women as a class, NOW contested discrimination against *low-mileage drivers*, who just happened to be (disproportionately) women.[38] By centering low-mileage drivers as the class harmed by insurers' pricing practices, feminist activists paradoxically attempted to "de-moralize" the insurance controversy (cf. Simon, 1988), shifting away from politically charged discussions of gender identities to the presumably irrefutable terrain of sterile statistics. But there was a problem with this strategy – as much as NOW did not want to look at drivers as "sex-classes," it was difficult to avoid doing so. Regulators quickly objected to NOW's arguments, noting that rather than gender operating as a proxy for mileage, feminists were attempting to use *mileage as a proxy for gender*.[39] NOW activists, for their part, could scarcely refrain from referencing "low-mileage" or "high-mileage drivers" without modifying these categories as pertaining to "women" and "men."[40] Apparently, mileage made sense as marking a legal class and forming a political constituency only when refracted through the prism of gender difference.

In the end, regulators prohibited the use of gender classifications in pricing auto insurance in the state of Pennsylvania, but were *not* convinced by NOW's lawsuit

[34] "Complaint: Pennsylvania NOW versus State Farm," September 23, 1986, MC 666, Folder 4, Box 363, NOW Records.

[35] "Plaintiffs' Brief in Opposition to Defendants' and Insurance Department's Motions for Stay of Proceedings, More Specific Pleadings, and Dismissal of Plaintiffs' Claims," November 21, 1986, MC 666, Folder 1, Box 132, NOW Records.

[36] "Letter to Sally Burns from Deborah Ellis," November 19, 1987, MC 623, Folder 2, Box 128, NOW Records; "Women's Groups Split on Unisex Car Insurance Rates," *The Pittsburgh Press*, September 23, 1988.

[37] "Dialogue on Pennsylvania NOW's Auto Insurance Sex Discrimination Lawsuit," September 23, 1988, MC 496, Folder 23, Box 117, NOW Records; "Some Thoughts on True Equality," *Allentown Morning Call*, October 2, 1988, MC 496, Folder 23, Box 117, NOW Records.

[38] "Press Strategy and Analysis, PA NOW Auto Insurance Case," October 14, 1986, MC 666, Folder 4, Box 363, NOW Records.

[39] "Women's Groups Split on Unisex Car Insurance Rates," *The Pittsburgh Press*, September 23, 1988.

[40] "Perspective on Automobile Insurance Pricing," Presented by Patrick Butler at the National Conference of State Legislatures Conference on the Crisis in the Insurance Market, Boston, Massachusetts, February 24, 1989, MC 663, Folder 14, Box 24, NOW Records.

that insurers ought to also be required to price on the basis of mileage driven.[41] NOW's failure to reorganize auto insurance pricing around mileage was a predictable result of the manner in which existing classification schemes were endowed with a "high ontological status" (Shilton, 2012: 390–91), privileging the characteristics selected to define classes as reflecting objective "truths about the world." In other words, whatever characteristics already in use to predict an outcome would seem self-evident, making it difficult for alternative classifications (and the groups they referenced) to gain traction.[42] Of course, such difficulties were compounded when already established classifiers carried salient group identities that amplified their "ontological status." In this regard, ironically, potent group identities were reinforced, not diminished, by the legal contest between insurers and NOW: the very logic of "subsidy" that underpinned arguments on both sides of NOW's lawsuit suggested that only a sociologically meaningful group could absorb (or impose) costs from (or onto) another such group. Ultimately, the fact that "low-mileage drivers" subsidized the costs of "high-mileage drivers" mattered only because "women" subsidized "men" (see Krippner, 2021).

Accordingly, while gender was suppressed as a classifier in insurance pricing, gender difference continued to organize the distribution of benefits and harms between men and women in ways that remained obvious to activists. Women's disadvantage was not lost from view *even in a unisex system* since it was understood that real differences between men and women's driving behavior would be reflected in different levels of risk, regardless of whether those differences were made visible in insurers' classification system. In fact, this was what NOW decried as "false unisex": a pricing system in which gender classifications were removed but women continued to be disadvantaged because the underlying social conditions that produced gender difference were not addressed.[43] As such, while NOW's litigation against State Farm was itself not successful, feminist activism against insurers continued apace in other states and in other lines of insurance (see Heen, 2014; Krippner, 2021). What is most important for understanding this outcome, we suggest, is that class-based systems of pricing attach individuals (conceived as whole persons) to groups whose members are imagined to share certain salient features in common. Critically, the mutual constitution of group and individual facilitates a shared subjectivity that enables collective mobilization, embedding the group identity within the pricing mechanism even under circumstances in which it is not directly visible to participants. As we show in the next section, this situation is starkly different in attribute-based systems of classification, which not only suppress but also *scramble* group identities, making collective mobilization considerably more difficult.

[41] PA. N.O.W et al. v. PA. Ins. Dept, 122 PA Commw 283 (1988).

[42] As Barbara Brown and Ann Freedman (1975: 46; emphasis added) observed, "As long as the insurance companies group people on a basis that has some consistent predictive value, the group experience will seem correct, and *it will be difficult for those who constitute a subgroup with a different risk to identify themselves as such.*"

[43] "Dialogue on Pennsylvania NOW's Auto Insurance Sex Discrimination Lawsuit," September 23, 1988, MC 496, Folder 23, Box 117, NOW Records; "Some Thoughts on True Equality," *Allentown Morning Call*, October 2, 1988, MC 496, Folder 23, Box 117, NOW Records.

Attribute-based pricing in credit markets

Creditors are also in the business of classification, but their objective in classifying is not to constitute groups of individuals who share select characteristics in common, but rather to give each individual her own *distinct* risk classification (Morris, 1966: 54). Since the 1970s, the practice of credit scoring has been the main tool used by lenders in the United States to accomplish the sorting of risks in credit markets (see Fourcade & Healy, 2013a; Hyman, 2011; Krippner, 2017; Poon, 2007, 2012). Anyone who has applied for a mortgage or car loan will likely be familiar with the credit score, which determines an individual's eligibility for credit, as well as the interest rate paid on the loan. A brief discussion of how creditors use the information contained in a scorecard like the one represented in Fig. 2 to calculate a credit score will help to distinguish this form of classification from the insurance pricing table examined above.[44]

The purpose of the credit score is to predict the risk of default on a loan so that creditors can make appropriate decisions about who should receive credit and what interest rate they should be charged. To create a credit score, creditors cull data from loan applicants to construct an index composed of 8–12 different characteristics, such as time with current employer, rent or own home, type of occupation, and so on. Notably, these various characteristics need not be causally related but merely correlated to the risk of default (Johnson, 1992). Each characteristic is assigned a point score depending on how much it adds to the predictive power of the entire index. New applicants for credit are evaluated on each item and assigned the indicated number of points. These points are then added together to calculate a total score determining payment potential (Myers & Forgy, 1963: 799). Those achieving a score above a given cutoff receive credit; those below that threshold are denied credit (see Hsia, 1978; Lewis, 1994).

We refer to this pricing technology as "attribute-based" because an individual's score is a tally of her values on a series of variables.[45] Unlike class-based systems that define an average value for a *group* or *class*, attribute-based systems attempt to give each individual a unique value or price, as closely as this can be approximated.

[44] We discuss credit scoring here as it was practiced when first widely adopted in the 1970s and not as the technique subsequently evolved in later decades. The most critical development in this regard involved the shift beginning in the second half of the 1980s from custom scorecards constructed from each user's own loan files to generic (FICO) scores generated from credit-bureau data. This shift coincided with new uses of credit scores that were no longer applied simply to the decision to extend or deny credit, but also used to determine variable prices for loan products (i.e., risk-based pricing). As Martha Poon (2007: 300) notes, the development of generic scores produced an object that was even more fully decontextualized compared to custom scorecards: "In circulating everywhere, in appearing as the same kind of number, in being perpetually recalculated, consumer credit risk calculation is no longer anchored in particular moments or specific places." Notably, this process of decontextualization has only increased with the advent of "big data," amplifying and accelerating the processes we describe here. We consider the implications of our argument given more recent developments in artificial intelligence and machine learning in the conclusion.

[45] We could also refer to this decision-making technology as "variable-based." We prefer *attributes* to *variables* because it is the language that creditors themselves use to describe an item of information about an applicant. More precisely, "attributes" are possible values on the variables scored by creditors (e.g., "homeowner" is an attribute of the variable "type of residence"; "18–25" is an attribute of the variable "age"; and so on) (see Lewis, 1994).

Example of Application Scoring Table

Years on Job	Less than 6 Months 5	Six Mos to 1 Yr 6 Mos 14	1 Yr 7 Mo to 6 Yr 8 Mo. 20	6 Yrs 9 Mo to 10 Yr 5 Mo. 27	10 Yrs 6 Mos or More 39	
Own or Rent	Own or Buying 40	Rent 19	All Other 26			
Banking	Checking Account 22	Savings Account 17	Checking and Savings 31	None 0		
Major Credit Card	Yes 27	No 11				
Occupation	Retired 41	Professional 36	Clerical 27	Sales 18	Service 12	All Other 27
Age of Applicant	18 to 25 19	26 to 31 14	32 to 34 22	35 to 51 26	52 to 61 34	62 and Over 40
Worst Credit Reference	Major Derogatory -15	Minor Derogatory -4	No Record -2	One Satisfactory 9	Two or More Satis-factory 18	No Investig. 0

Fig. 2 Attribute-Based Pricing (Credit Scorecard). Source: Lewis (1994)

Scoring technologies have now proliferated across social domains: they are used to assess one's attractiveness to a potential mate in on-line dating platforms; to determine the books Amazon thinks you might most like to read; and to indicate your genetic risk for developing a particular disease or condition. Perhaps most controversially, scoring technologies are used to determine an individual's risk of recidivism in making decisions about sentencing and parole, among many other applications (e.g., Brayne, 2020; Brayne & Christin, 2021; Eubanks, 2018; Fry, 2018; Hirschman & Bosk, 2020; O'Neil, 2016; Pasquale, 2015; Starr, 2014).

Notably, a cell in the credit scoring table does not contain a group of individuals who share a series of characteristics in common, nor even a single individual, but rather an *attribute*. In other words, credit scoring operates on variables, not on persons; each individual loan application is mined for data rather than preserved intact. As a result, credit scoring systems display a bewildering combinatorial logic: if a particular individual is denied credit, this is a result of her particular values ("attributes") on 8–12 different variables; another individual with *the same credit score* almost certainly arrived at the score through some different combination of values on those variables. Thus, two individuals with the same credit score may share an outcome (being denied access to credit), but they do not share a social experience, *as they may not hold any sociologically meaningful characteristics in common*. In this regard, Simon's (1988) observation that actuarial systems place individuals in cells that do not correspond to lived social meaning appears to describe credit scoring better than it does risk classification in insurance. While the cell in the insurance pricing table is "artificial" in the sense that it is constituted by a statistical operation rather than an actual social relationship, legible social categories still define the construction of classes. In contrast, my credit score joins me not with individuals with whom I share certain characteristics in common, but simply *other individuals who have the same score as I do*. This is a much more abstract form of classification, one that deeply obscures social relationships and fetishizes the score itself (see Fourcade, 2016).

To appreciate the implications of this more fully, consider the individual who is classified by the credit score: she might have two years of experience with her current employer, hold a major credit card, rent her current residence, and work in the retail field, among other characteristics. Unlike in insurance pricing, the scoring table does not attempt to identify a *group* of individuals who share all these characteristics in common. Instead, the scoring model provides an estimate of the incremental contribution of each *variable* included in the model to an individual's likelihood of default. Because no fixed group is constructed, variables can be swapped in and out of scoring models for other predictors with some degree of flexibility.[46] If another set of predictors proves more informative, for example, creditors can replace those currently in use. Similarly, if a particular variable comes under scrutiny by regulators, creditors can easily substitute a proxy variable (Krippner, 2017).

This feature of credit scoring, it should be noted, is very much by design. These systems came into vogue in response to anti-discrimination laws passed in the 1960s and 1970s, largely because scoring techniques made it possible for creditors to dispense easily with social categories that had run afoul of new legal prohibitions (see

[46] There are two distinct issues at play here. First, as a purely technical matter, because creditors analyze data on variables rather than whole persons, even relatively small samples generate sufficient observations to calculate reliable estimates (provided certain independence assumptions hold). This affords creditors considerable flexibility in constructing scoring models especially when compared to insurers, whose reliance on cross-classified data significantly increases the number of observations needed to generate reliable estimates (see footnote 15). Second, the "risk pool" in credit markets is defined by a common score (see Morris, 1966: 55), with no expectation that the individuals who share risk (i.e., pay the same price for credit) hold characteristics in common *other than* the achieved score. In insurance, by contrast, the risk pool is constituted by the *class*, which is assumed to be formed by individuals who hold a series of risk-relevant characteristics in common. The expectation that insurance risk classes are constituted by individuals who represent the "same" risk significantly constrains the selection of variables used to construct classes, as we have already noted. Critically, there is no analogous constraint on creditors. In fact, the cells in the credit scoring table can be collapsed for statistical expediency, regardless of whether the resulting groupings make sense in some larger sociological sense (see Lewis, 1994: 55–58). Thus, creditors are not required to select variables that ensure that individuals are "fairly" grouped in the same way as is true for insurers.

Hyman, 2011; Krippner, 2017; Poon, 2012). Rather than place individuals in overly broad social categories, scoring technologies allow the proliferation of risk classes, producing ever-finer classifications that conform more closely to individual experience.[47] In this regard, credit scoring seeks to effectively "close the gap" between category and person, with each person potentially occupying her own unique category and receiving her own custom price. As a result, membership in groups defined by race, ethnicity, gender, sexuality, and so on is no longer directly visible in the score (cf. Fourcade, 2016). As we show below, the articulation of shared political grievances is highly unlikely in a context where categorical memberships are no longer salient. To reiterate the key point however, this is not only a function of the manner in which scoring systems make particular group identities organized around race, ethnicity, gender, and sexuality less visible (a feature that may be shared with class-based systems that can also operate to suppress particular group identities), but even more fundamentally it is a consequence of how scoring systems detach individuals from groups (identified on any basis) altogether (see Marron, 2007: 111).

NOW's credit campaign

This is what the history of political contestation over access to credit demonstrates, which conveniently for our analysis involves the same organizational actors as in the insurance case. In the early 1970s, the National Organization for Women began to direct its attention to problems of credit access, asserting that creditors' reliance on sex and marital status to determine eligibility for credit constituted a form of illegal discrimination.[48] At the time, women faced significant obstacles gaining access to credit without a husband's or father's approval – and *his* signature on the loan application (Hyman, 2011; Thurston, 2018; Trumbull, 2014). In response to these difficulties, NOW created its "Credit Task Force" to lobby for the passage and oversee implementation of the Equal Credit Opportunity Act of 1974. This landmark anti-discrimination legislation prohibited creditors from relying on sex or marital status in making decisions about credit.[49] The Equal Credit Opportunity Act's effectiveness in addressing gender discrimination, however, was impeded by the widespread adoption of credit scoring in response to the passage of the new law (Hyman, 2011; Marron, 2007; Poon, 2012).

To understand why this would be the case, consider that when the passage of the Equal Credit Opportunity Act made the use of gender classifications illegal, credit scoring techniques allowed creditors to substitute proxy variables for gender and other protected classes (Krippner, 2017). The variable "sex" disappeared from credit scoring models, for example, but was quickly replaced by telephone in the home (almost invariably listed under the name of the husband), occupation, part-time/full-time employment status, homeownership, income, and a multitude of other variables closely correlated

[47] This was often claimed as an advantage of credit scoring over the more subjective forms of credit screening it displaced (see Johnson, 1992), but it applies equally well to a comparison with class-based methods of pricing risk such as used in insurance markets.

[48] The following discussion draws on Krippner (2017).

[49] Race, ethnicity, national origin, religion, and other protected classes were added to the statute in amendments passed in 1976.

with gender. Thus, from the perspective of creditors, the advent of credit scoring not only made it relatively painless to comply with the requirements of anti-discrimination law, but also had the additional advantage of suppressing socially meaningful group identities, making it much more difficult for those denied access to credit to contest the terms of their exclusion (Krippner, 2017; Marron, 2007; Poon, 2012).

Of course, feminist credit activists were well aware that many of the variables routinely scored by creditors included thinly veiled proxies for sex and marital status. As the Chair of NOW's Credit Task Force pointedly observed, "NOW is very skeptical of alleged relationships between creditworthiness and characteristics that also happen to be associated with being female."[50] In this sense, feminists bore no illusions that the introduction of credit scoring had eliminated discrimination *tout court* from credit markets. But while NOW activists were savvy to ongoing discriminatory practices following the passage of the ECOA,[51] they were also keenly aware of how the implementation of credit scoring would make it difficult for women applying for credit to identify discrimination when it occurred – a feature of credit scoring openly embraced and celebrated by creditors (e.g., Brandel, 1976; Lewis, 1994: 14).

A key consideration here was the complexity of credit scoring compared to the "judgmental" systems of credit screening it displaced (as well as to systems of insurance pricing considered in the previous section).[52] Credit scoring is a pricing technology in which "[t]he credit risks associated with each … [scored characteristic] must be combined to ascertain the credit risk associated with any one person" (Brandel, 1976: 88). Thus, the credit score creates a dizzying number of possible permutations: even a relatively simple scoring system, such as the one introduced by Montgomery Ward in the 1960s, defined approximately 750,000 possible combinations of factors (ibid.: 88). As such, the massive size of this classification system made the meaning of the score difficult to comprehend (Krippner, 2017).

Beyond the sheer number of possible combinations, another element of the credit score's complexity involved how this technology formed groups. Unlike the class-based pricing techniques used in insurance, in which any given individual was a member of one of a finite number of classes organized around a few legible (and usually quite stable) social categories, the underlying premise of credit scoring was that an individual belonged not to a single class but to many different "subgroups" in society (Brandel, 1976: 88). More specifically, each individual straddled numerous distinct subgroups corresponding to the various characteristics scored: occupation, time with employer, number of bank accounts, and so on. Each of these subgroups might involve *a different subset of individuals* (i.e., there was no necessity for the *same* individuals to occupy a cell defined by employment in the retail sector, another

[50] Letter to Federal Reserve Board from Cynthia Harrison, June 5, 1979, Folder 18, Box 1, Cynthia Harrison Papers, Schlesinger Library, Radcliffe Institute, Harvard University, Cambridge, MA.

[51] Letter to State Coordinators from Cynthia Harrison, July 25, 1978, Folder 28, Box 45, Cynthia Harrison Papers.

[52] So-called "judgmental" credit screening involved a face-to-face interview in which creditors weighed relevant factors subjectively, often relying on "gut feelings" to produce a decision (Stuart, 2003).

defined by having two years of experience on the job, a third defined by holding both a savings and checking account, and so on).[53] Needless to say, these cross-cutting affiliations undercut any coherent or actionable sense of group membership (cf. Marron, 2007: 111). At issue then was less the suppression than the *scrambling* of socially meaningful group identities for purposes of collective identification.[54]

Given the opacity and complexity of credit scoring systems, following the passage of the ECOA, feminist credit activism was primarily focused on establishing regulatory rules that would make it easier for women denied credit to detect discrimination when it occurred. The original legislation required only that a creditor who denied an application for a loan give the unsuccessful applicant specific reasons for this decision or inform her that she had the right to request these reasons.[55] Feminists took issue with the fact that a woman denied credit did not automatically receive reasons for the denial but had to request them in writing.[56] Even more troublesome was that creditors who denied an application for credit were required to report only four reasons for their negative decision, without any guidelines governing how these four were to be selected from among the myriad variables evaluated by scoring systems. Most notably, creditors were not required to list the four factors on which applicants had lost the greatest number of points, but could report *any* item used in a scoring model, even those that were relatively unimportant in determining the ultimate outcome of an application.[57] Feminists naturally worried that creditors would use such loose reporting requirements to mask discriminatory practices.

In general, NOW questioned "the need for a credit scoring system composed of many and complex elements to determine who constitutes a good risk."[58] Instead, feminist credit activists demanded that scoring systems be constructed using a limited number of well-defined characteristics that could be easily explained to rejected applicants for credit.[59] In this regard, NOW activists were particularly concerned that the standard reasons provided by creditors to explain why an application had

[53] As a result, when an individual's score was tallied across these various characteristics, she might land in a "group" that contained only one person. While such a result would signal the *failure* of insurance classification – because group experience could not be statistically validated on the basis on one observation – it was in effect the aspiration of credit scoring systems to place each individual in her own class. Nothing better illustrates the different ontologies of insurance and credit – *class* versus *attribute* – than the fact that having too few individuals in a class caused endless handwringing in insurance (e.g., Casey et al., 1976) but was a prime objective of credit scoring (Morris, 1966: 54).

[54] Put differently, even if gender were not expressly prohibited as a pricing variable, the way scoring models refract an individual's group membership across multiple categories such that one is not placed in a single, overarching class with others would make collective mobilization more difficult in the credit scoring context compared to insurance pricing.

[55] "Proposed Rulemaking, Federal Reserve System, Equal Credit Opportunity: Application to Credit Scoring," Folder 18, Box 1, Cynthia Harrison Papers.

[56] Federal Reserve Board Hearings on Proposed Regulations to Implement the Equal Credit Opportunity Act, Statement of National Organization for Women, July 14, 1975, Folder 22, Box 1, Cynthia Harrison Papers.

[57] "Proposed Rulemaking, Federal Reserve System, Equal Credit Opportunity: Application to Credit Scoring," Folder 18, Box 1, Cynthia Harrison Papers.

[58] Letter to Federal Reserve Board of Governors from Cynthia Harrison, August 21, 1979, Folder 18, Box 1, Cynthia Harrison Papers.

[59] Letter to Federal Reserve Board of Governors from Cynthia Harrison, August 21, 1979, Folder 18, Box 1, Cynthia Harrison Papers; Letter to Federal Reserve Board of Governors from Edith Canty, June 15, 1979, Folder 19, Box 1, Cynthia Harrison Papers.

been declined were "vague" and "confusing."[60] A typical rejection letter from a creditor indicated items such as "type of residence grouping," "length of time on job," "types of credit accounts," and "insufficient credit file."[61] Without further elaboration on how these various criteria were defined, "[t]he woman remains in the dark as to what she must do to rectify her situation."[62] Feminist credit activists were especially adamant that rejected applicants receive full information on *all* of the variables scored by credit models, not merely the four items required by regulators.[63] "Because these systems tend to be complex," NOW asserted, "applicants have the right to know *every instance* in which they failed to achieve the maximum number of points."[64]

Notably, even aided with such information, it was not easy to construct definitive "proof" of discrimination: if an applicant for a loan missed the cutoff for approval by a few points, an additional point on any one of a number of variables could put her above this threshold. Accordingly, even if she lost a disproportionate number of points on a particular variable that served as a close proxy for sex or marital status, it was difficult to conclude that this item *caused* the denial as an additional point or two on *any other variable* might have resulted in a different outcome (Taylor, 1980). "There often is no specific reason [for the denial an application]," creditors proclaimed; rather credit scoring presumed that "[the] factors are interrelated [in such a way that] it would be inappropriate to isolate [any] one factor" (Demkovich, 1977: 356).

But if no single cause determining a creditor's decision could be identified, *neither could a single unitary subject (*i.e.*, "women") be constructed from the credit score*. In this sense, feminist activists who demanded full disclosure of each scored element were inadvertently drawn into the individualizing logic of creditors. In particular, while NOW's request that creditors provide declined applicants with full information on *all* of the variables scored might have made it more possible for an individual woman declined credit to remedy a poor score by taking action to improve her creditworthiness, it arguably made it more difficult to assemble a collective subject who was the victim of discrimination (cf. Moor & Lury, 2018). The greater the number of relevant factors determining credit outcomes, the more elusive this subject became. In this instance, then, feminist activism aligned well with the underlying premise of credit scoring, which tended to obscure structural features producing group disadvantage in favor of individual choice and circumstance (Fourcade, 2016; Fourcade & Healy, 2013b; Krippner, 2017).

60 Letter to Federal Reserve Board of Governors from Edith Canty, June 15, 1979, Folder 19, Box 1, Cynthia Harrison Papers.

61 Letter to Linda J. Wilt from M. McLay (New Accounts Department, J.C. Penney), June 20, 1979, Folder 2, Box 1, Cynthia Harrison Papers.

62 Letter to Federal Reserve Board of Governors from Cynthia Harrison, August 21, 1979, Folder 18, Box 1, Cynthia Harrison Papers.

63 Letter to Federal Reserve Board of Governors from Cynthia Harrison, June 5, 1979, Folder 18, Box 1, Cynthia Harrison Papers; Letter to Federal Reserve Board of Governors from Edith Canty, June 15, 1979, Folder 19, Box 1, Cynthia Harrison Papers.

64 Letter to Federal Reserve Board of Governors from Cynthia Harrison, June 5, 1979, Folder 18, Box 1, Cynthia Harrison Papers; emphasis added.

Thus, credit scoring operated to neutralize struggles around access to credit through two distinct, albeit interlinked mechanisms. First, the replacement of gender classifications with a series of proxies that proliferated risk classifications disorganized opposition to credit discrimination. Notably, when asked why mobilization around credit stalled a few years after the passage of Equal Credit Opportunity Act,[65] the former Chair of NOW's Credit Task Force at first appeared puzzled by the question. After a long, considered pause, she replied: "I guess the problem just kind of disappeared."[66] The language here is telling. Not the forthright assertion one might expect from an activist insisting that the legislation that NOW had championed effectively resolved the problem of credit discrimination, but a more muted statement that the issue had simply *slipped from view*. This captures, we suggest, something of the political logic of scoring devices.

Second, it was not only that credit scoring made gender less salient to activists who sought to combat discrimination in credit markets. In this risk pricing regime, an individual's position in social space was the result of her unique trajectory through the scoring apparatus, unlikely to be exactly matched by any other individual – one turn of the kaleidoscope rearranged the pieces, fragmented the picture, generated a new pattern. As Doncha Marron (2007: 111; emphasis added) observes, credit scoring treats "individuals *not as individuals* but as arrays of categorized attributes." The resulting fragmentation of personhood attenuates the experience of group membership, organized on whatever basis. As a result, the practice of credit scoring made it all but impossible to recognize one's shared condition with other similarly situated individuals, frustrating efforts to create robust and enduring forms of political mobilization (Krippner, 2017).

Discussion and conclusion

In this article, we have explored two distinct forms of classification used in pricing risk, each with different implications for the mobilization of political power in the age of the algorithm. In *class-based* systems of pricing, represented here by the insurance pricing table, individuals are firmly attached to legible social categories that may constrain (and even distort) individual experience, but also facilitate the shared subjectivities that make political action possible. Our first case demonstrated this paradox, as NOW's long-running campaign to end gender discrimination in insurance markets was enabled by the legibility of gender in insurers' risk classification schemes (see Krippner, 2021). It is particularly telling here that NOW's unsuccessful attempt to reorganize auto insurance pricing around mileage was read *through* gender by regulators and activists alike and, as a result, the putatively "demoralized" variable never lost the political charge associated with the more potent group identity (cf. Simon, 1988). In contrast, *attribute-based* forms of pricing, represented here by the credit score, detach individuals from sociologically

[65] NOW's Credit Task was abruptly disbanded late in 1979 (see Krippner, 2017 for a fuller history of the Task Force). Note to Cynthia Harrison from Barbara Duke, January 20, 1980, Folder 1, Box 1, Cynthia Harrison Papers.

[66] Interview with Cynthia E. Harrison conducted by Greta Krippner, August 24, 2010, Washington D.C.

meaningful groups, freeing individuals from oppressive social categories but also making political action more difficult to achieve. Accordingly, credit scoring systems have faced relatively few challenges, with these challenges tending to be self-limiting as they have typically involved demonstrations that a particular variable functions as a proxy for a prohibited category, resulting in the further removal of socially significant attributes in favor of those less likely to organize resistance (see Fourcade, 2016).[67] Our second case illustrated this dilemma, where in spite of NOW's effort to keep attention focused on ongoing gender discrimination in credit markets, feminist mobilization dissipated after credit scoring became firmly established among lenders (see Krippner, 2017). Underlying both these collective action problems are different ways of constituting individuals: the individual as *whole person* whose salient characteristics are articulated to those of the group; or the individual as an *array of attributes* who does not belong to or express any group identity.

Thus far, we have treated these two forms of classificatory systems symmetrically, as though one might simply "choose" between them. But these systems are not equally available as objects of choice; in fact, the insurance pricing table seems to represent the (analog) past – and the credit score seems to anticipate the (digital) future – of the politics of classification.[68] In this regard, the stable social identities that have long undergirded key institutions in our society have begun to break apart in recent years, giving way to greater fluidity and a sense of impermanence – a shift that historian Daniel Rodgers (2011) has aptly characterized as the "age of fracture." As Rodgers documents, this fracturing spans the domains of state power, sexuality, economy – and even the forms of risk classification in insurance markets discussed here, which increasingly are converging on the kind of scoring techniques pioneered in credit markets (see Kiviat, 2019), in which each individual is sorted and ranked based on a shifting configuration of behavioral attributes rather than membership in a fixed social group (O'Neil, 2016).

To fully make sense of the fractured social terrain of digital capitalism, it is useful to return once again to Simon's (1987; 1988; Feeley and Simon 1992) writings on "actuarialism." As we have seen, Simon's work anticipates our concerns here by analyzing how the proliferation of statistical techniques across social domains disabled particular forms of political activity in contemporary society. In particular, Simon noted that actuarial practices tend to place individuals in passive, artificially constructed groups, limiting potentials for collective mobilization. In this regard, Simon suggested that actuarial techniques have transformed Weberian status groups and Marxian classes into sterile "aggregates" unable to mobilize adherents effectively for purposes of political action. We have already seen that Simon

[67] This paradox is not entirely novel to the digital era, as Joshua Gamson (1995) long ago noted that anti-discrimination movements undermined the conditions necessary for their continued existence by attempting to eliminate from use the very same categories that were also the source of collective identification and political mobilization. What is arguably new in the digital era is the way algorithmic technologies *directly* weaken processes of group formation, arguably making Gamson's paradox all the more acute.

[68] More accurately, the future of the politics of the classification likely lies with artificial intelligence and machine learning – technologies that we expect to accelerate and amplify the trends we associate here with the early development of credit scoring. We elaborate briefly on this point in our discussion below.

underestimated the manner by which these "sterile" aggregates might actually organize political power, if in a more limited and narrow manner compared to traditional social movements. But a more serious limitation of Simon's analysis lies in his failure to distinguish actuarial techniques based on the creation of classes from those based on the calculation of individualized scores. Simon's conflation of what we refer to here as *class-based* and *attribute-based* forms of classification meant that he failed to apprehend a greater threat to our collective political life than the formation of "aggregates" – namely, the *dissolution* of aggregates (and with this dissolution, potentially, the dissolution of the individual as acting subject) (cf. Rouvroy, 2013; Rouvroy & Berns, 2013).

As we have seen, the groups (or aggregates) contained in the cells of the insurance pricing table may be passive, but these are still *potential* collectivities that can under particular circumstances be activated. In this sense, the groups constituted by actuarial techniques are reminiscent of feminist philosopher Iris Marion Young's (1994) attempt to characterize gender as kind of a "serial collective." Drawing on Sartre's (1976) description of individuals waiting for a bus, Young suggests that these bus-riders form a collective, albeit a latent one, minimally aware of each other's presence, and yet still aware enough to notice a shared condition should the bus not arrive on time. Rather than a deep sense of mutual identification (more typical of identity politics), it is a shared orientation to material objects (e.g., the bus) and social practices (e.g., the existence of regular schedules and routes) that constitutes this group (or "serial") as a collective.

Young's (1994) purpose in applying the notion of "seriality" to gender was to suggest that as a social category gender is more like the group of bus-riders – i.e., a passive orientation to a set of material conditions defined by physical objects and institutionalized social practices – than a deeply internalized sense of membership in a community formed by others whom I imagine are "like me." In this context, it is now possible to understand more fully why Simon (1988) treats actuarialism as inherently depoliticizing: the statistical techniques used to sort individuals into classes are material-practical conditions that position (gendered) social actors as serial collectivities rather than as self-conscious groups formed around a potent social identity. We are also now in a position to understand more clearly why Simon overstates his case: while serial collectives (or aggregates, to use Simon's terminology) are largely passive, they are not necessarily so, because what bus riders – like individuals of the same gender – share is the experience of traveling together on a regular route. If travel along this route is disrupted, members of a serial collective will immediately perceive their commonality – and may be in a position to act on this commonality by constituting themselves as a group with a shared identity and purpose.

Simon (1988), of course, would not necessarily disagree with this: he states that actuarialism makes political action less likely, not impossible. To reiterate, we fault Simon not for overblowing the dangers of actuarialism, but for *misidentifying* these dangers by failing to distinguish between one classificatory technology in which individuals are treated as members of (passive) groups and another classificatory technology in which individuals are not positioned in relation to any group at all. In this regard, algorithmic scoring systems constitute a classification technology that is *not* conducive to the formation of serial collectivities along the lines we have just discussed. Rather than placing individuals in classes (or aggregates) with others, the objective of scoring is ultimately to give each individual her *own* unique value or price; in a fully elaborated scoring system, each individual would occupy a cell *alone*. To return to the analogy we have been using, these are not individuals riding a bus together, but each driving their own private vehicles. Moreover, we are now dealing with a system with no fixed transportation grid, no established rules regarding traffic flow, and no regular route of travel. Here then is where we really have to worry about the depoliticizing tendencies of "actuarialism."

In this sense, Simon (1988: 788) is rightly concerned that "group subjecthood" may be difficult to achieve in an actuarial society. However, the class-based actuarial techniques he is primarily concerned with in his analysis leave the most critical condition supporting group subjecthood – namely, *individual subjecthood* – largely intact. It is true that, as Simon (1988: 794) notes, the insurance pricing table addresses persons only in terms of ("demoralized") formal attributes rather than social identities that have "moral density" (cf. Austin, 1983). But insofar as these attributes position individuals similarly with respect to a series of material and practical constraints (in this instance determined by the actuary's calculations), they may in fact generate identities that can become "morally dense" when social systems fail to accord with expectations. The key here is that actuarial techniques create classes in which individuals sharing these attributes are held together in a group – *even an artificial one* – with the result that the formation of "serial collectives" remains an active possibility.[69]

Now consider how the advent of scoring technologies alters these circumstances. First, scoring technologies actively suppress those characteristics (e.g., race, gender, sexuality, etc.) with the greatest potential to acquire "moral density," leaving behind only the vaguest trace in the proxy variables substituted for them.[70] Second, scoring technologies do not hold individuals in groups (even artificial ones), but strive to place each individual in her own distinct "class." This is the sense in which scoring technologies are often said to herald a new "individualization" or "personalization" – with systems of statistical classification moving ever more closely to knowing each individual as singular and unique (see Barry & Charpentier, 2020; Bouk,

[69] Rebecca Elliott's (2021) work on the Federal Emergency Management Agency's (FEMA) flood insurance program provides an instructive example here. As Elliot discusses, FEMA's restructuring of its risk classification scheme created a group constituted by a new category of person, the "flood zone homeowner." This was an "artificial" group to be sure, and yet when Hurricane Sandy visited destruction on those joined together by FEMA's new classification, they found a shared identity and a common political purpose expressed in mobilization to "Stop FEMA Now!" As Elliott (2021: 121) pointedly notes, "[T]he flood insurance rate map did not displace or defuse contestation; it instead helped to activate and organize it."

[70] Notably, class-based technologies may also involve the suppression of salient social identities such as race or gender. But as we observed in our analysis, the operation of forming classes itself tends to allow these identities to "show through" even in circumstances when they have been formally eliminated from classification schemes, thus maintaining potentials for collective identification.

2015; Cevolini & Esposito, 2020; McFall, 2019; McFall & Moor, 2018; Moor & Lury, 2018).[71] But as the individual becomes more "singular," shared social identities are scrambled, making group affiliation more difficult to achieve. Indeed, in a fully implemented scoring system, a common score level may be the *only* characteristic shared among a group of individuals, eroding the capacity to imagine the social world in terms of collectivities (see Barry, 2019; Barry & Fisher, 2019).

This is where we see newer technologies associated with artificial intelligence and machine learning accelerating the dynamics we have associated in this article with attribute-based forms of classification.[72] While the first generation of credit scoring models discussed here scrambled social identities by virtue of creating "groups" in which individuals do not necessarily hold any sociologically meaningful characteristics in common, the resulting groupings were still relatively static. Accordingly, while a given individual's pathway to a particular score may have been unique, the coordinates determining that trajectory were held constant with each "draw" from the data. But this is no longer the case with machine learning models, where each query to a statistical database rearranges the elements determining a decision, resulting in a novel configuration of "groups" or "profiles" (Cheney-Lippold, 2017; Rieder, 2016; 2020; Rouvroy, 2013; Rouvroy & Berns, 2013; Ruppert, 2012). In this context, the relevant concern is less that members of groups do not share any sociologically significant characteristics in common than it is the continual *churning* of group membership defined on whatever basis. In this brave new world, as Bernhard Rieder (2016: 49; emphasis added) notes, "[t]he notion of the group ceases to be a stable analytical category and becomes a *speculative ensemble* assembled to inform a decision and enable a course of action. … Ordered for a different purpose, the groups scatter and reassemble differently."

The continuous "updating" of machine learning models is not the only impediment they present to processes of group formation, however. In addition, these models draw on massive quantities of data drawn from heterogeneous sources, confounding human efforts at interpretation (Burrell, 2016: 5). In the case of credit, alternative (or "fringe") lenders analyze thousands of data points for each individual borrower in order to select hundreds of variables to use in the final scoring decision (in contrast to the 8–12 variables used in the scorecards of the period we focused on in our analysis) (Hurley & Adebayo, 2016: 153; ZestFinance, n.d.). Whereas the traditional FICO score is constructed from a limited number of variables reflecting payment history, outstanding debt, credit history, new credit, and types of credit (Robinson + Yu, 2014: 9), an alternative lender might generate a score using data mined from sources far removed from the individual's credit use, ranging from non-credit payment streams (e.g., rent, utility, and phone bills) to so-called "behavioral" data (e.g., social media accounts, patterns of online activity, geo-location data, public records such as traffic tickets and legal proceedings, etc.) (Hurley & Adebayo,

[71] This "statistical individual" is something of an oxymoron insofar as the invention of statistics as a technique of social analysis abstracted away from individual particularities (see Desrosières, 1998; Hacking, 1990; Porter, 1986).

[72] By "machine learning" we reference a range of computational techniques iteratively applied to data to identify patterns in order to make predictions and inform decisions (Hurley & Adebayo, 2016: 160–61).

2016: 164–65; Robinson + Yu, 2014: 15).[73] Because these models are proprietary, potential borrowers will not know the basis on which an application for credit has been evaluated, making it difficult to find common cause with others who are similarly evaluated (Aitken, 2017: 18; Hurley & Adebayo, 2016: 179). Of course, credit scoring models have always been proprietary, and the minimal reporting requirements imposed by regulators have long been considered inadequate to give consumers' actionable information to contest an adverse credit decision.[74] Nevertheless, there is a qualitative difference between a proprietary model based on a finite number of variables and known data sources versus machine learning models that proliferate variables without limit and draw on diverse data sources not known to regulators or consumers (Robinson + Yu, 2014: 22; cf. Burrell, 2016). Thus, given the complexity and opacity of machine learning systems, we expect that as they are adopted for use across social domains they will amplify the processes we have identified, further inhibiting potentials for collective mobilization.

This is not to suggest that group formation has ceased altogether in the age of the algorithm.[75] Notably, in an increasingly scored world, groups may form around the structured *life chances* produced by the score: access to affordable housing, fairly priced credit, secure employment, and so on. In other words, rather than groups being defined by *inputs* to the scoring algorithm (i.e., socially salient characteristics shared with others), here we posit that the *outcome* produced by the score is what matters for group formation and attendant forms of political mobilization (e.g., inability to secure housing, being denied access to credit, the experience of employment discrimination, etc.). Indeed, in instances where scoring technologies shape life chances in particularly salient ways, the *score itself* may emerge as a sociologically meaningful object, serving as a focal point for mobilization. The clearest example here is the *subprime borrower* – a collective identity (constituted by individuals having a credit score less than 670) called into existence by credit scoring algorithms (Reid, 2017). But to date, tellingly, the subprime borrower is mostly notable for her relative absence as a political actor in the wake of the financial crisis.[76] More generally, while there have been scattered movements organized around various social outcomes mediated by scoring technologies (e.g., Appel, 2015; Kiviat, 2019; König & Wenzelburger, 2021), we are largely convinced by Marion Fourcade

[73] These techniques, it should be noted, are still experimental in credit markets, where the vast majority of credit decisions continue to rely on FICO scores calculated using more conventional statistical techniques (Hurley & Adebayo, 2016: 155). Jenna Burrell (2016: 11) reports that the company that produces the FICO score has for now avoided adopting machine learning techniques in part because of the difficulty of interpreting the resulting score. Thus, if these techniques represent the future of scoring technologies, this future has yet to fully arrive in credit markets, and appears even more remote in insurance given fundamental tensions between class-based ontologies and "individualized" pricing methods (see especially Barry & Charpentier, 2020).

[74] See discussion of NOW's credit campaign above.

[75] We are indebted to Roi Livne for the discussion in this paragraph.

[76] Given the social salience of the events that produced the subprime mortgage crisis, the geographic concentration of resulting foreclosures, and the clear discriminatory nature of lending practices (connected to a longer history of such discrimination), we would consider the identity of the subprime borrower especially propitious for political mobilization. In fact, it is difficult to imagine conditions that would be *more* likely to produce mobilization by a category of persons joined together by a common score, leaving us doubtful that other such mobilizations will materialize in less propitious circumstances.

and Kieran Healy's (2013a; 2013b) analyses that the manner in which especially recent incarnations of scoring technologies foreground individual behavior and choice tends to obscure the structural conditions that produce group disadvantage (cf. Krippner, 2017). Accordingly, we anticipate that it will be difficult to organize and especially sustain opposition to scored life chances as they will increasingly appear to be the product of purely individual circumstances: poor character, deficient judgment, or simple bad luck.

We further anticipate that where such movements do take hold, they will tend to pursue demands to "perfect" the algorithm by removing group-based biases of various kinds (cf. Ettlinger, 2018). These efforts may take the form of claims that "thin file"/unbanked individuals *could* be good credit risks if alternative (i.e., non-credit related) behaviors were taken into consideration (Wherry et al., 2019) or claims that minority borrowers encounter predatory lenders who deny them access to conventional loans corresponding to their achieved scores (Massey et al., 2016; Taylor, 2019). They may also take the form of intensifying calls to "audit algorithms," reverse engineering proprietary scoring models in order to identify – and ultimately eliminate – the biases they contain (Sandvig et al., 2014). Notably, these various attempts to purify the implementation of scoring technologies will likely serve to entrench rather than disrupt the logic of the score.

Thus, while not denying that scoring systems potentially open new possibilities for political mobilization, we nevertheless remain skeptical regarding what this politics will ultimately produce. Scores have not yet become identities that could supplant the traditional forms of social affiliation that they have displaced, and in an important sense, *they are designed not to do so*, weakening identity-based political mobilization.[77] Because scoring technologies decenter the social identities that have long formed the basis of civil-rights style mobilization, and these technologies also make any alternative basis on which a mobilizable identity could be forged fragmentary and fleeting, we do not envision mobilization in the digital future that looks like what we have known in the analog past. In this regard, we should ask what kind of politics is available when the social identities that anchor individual subjectivities are actively suppressed and the organizational technologies that create groups (on any basis) are disrupted. To return to the question with which we motivated our essay, what kind of person is summoned to act, if she is, by "individualized" systems of rating, ranking, and sorting?

Sociology's founding insight, beginning with Durkheim (2014 [1893]: 217-18), was that the collective constitutes the individual.[78] From this perspective, scoring systems represent a profoundly anti-sociological device, threatening to unravel

[77] An important counterpoint here is the way other kinds of algorithms than those we consider here may encourage identity-based political mobilization. We have in mind here recommendation systems that curate content on social media platforms, contributing to the resurgence of identity-based politics in its most virulent form (see Bail, 2021). We are intrigued by the relationship between algorithms that dampen and amplify group identities as a basis for political mobilization, but fully exploring this relationship is beyond the scope of the current article.

[78] This, of course, is not the only way of imagining the relationship between individual and collective in sociology. For an alternative to the conventional view that is particularly amenable to the digital age, see Bruno Latour's (2002; 2010) generative exploration of the social theory of Gabriel Tarde.

the seamless unity that previously characterized sociology's preconceptions of the social world, the statistical tools used to map that world, and the society those tools helped to construct (Ewald, 2020; cf. Rosanvallon, 2000). In opening a potentially unbridgeable gap between, on the one hand, our sociological preconceptions and statistical tools and, on the other hand, our lived experience of the social world, scoring systems present not only a problem in the sociology of knowledge but also a problem in the domain of social practice. In this regard, the way scoring systems both suppress and scramble the social categories that provide essential coordinates for navigating the social world makes it increasingly difficult to find those with whom we share similar material-practical conditions because, in a fundamental sense, *we do not find ourselves* (Butler, 2000: 59, 61).

The shifting play of attributes in the scoring table, serially reconfigured as the individual moves through life – or in more recent iterations of scoring systems, through the moments of the day – may loosen the hold of the rigid divisions that elsewhere demarcate social space. But the denizen of the scoring table, constructed in a combinatorial fashion from free-floating fragments of data, does not appear to have a narrative identity or coherent sense of self,[79] much less the capacity to act in concert with others on this basis (cf. Cheney-Lippold, 2017). In this sense, as Rouvroy (2013: 145) observes, algorithmic technologies increasingly bypass the subject, operating instead on infra-individual bits of data and supra-individual statistical "profiles" assembled from these data. Accordingly, we have to consider the troubling possibility that scoring technologies have not only dislodged the individual from larger social structures, but may have also dissolved the individual as a meaningful carrier of social action altogether (cf. Moor & Lury, 2018). If this is the case, these technologies portend a deeper kind of depoliticization than we might have imagined possible in confronting the oppressive social aggregates of a prior time.

Data sources

Archival data collections

The following are archival collections used in this research:

Schlesinger Library, Radcliffe Institute, Harvard University, Cambridge, MA
Cynthia Harrison Papers, 83-M238
National Organization for Women Legal Defense and Education Fund Records, MC-623
National Organization for Women Records, MC-666
National Organization for Women Records, MC-496

[79] In insisting here on narrative identity as a constitutive feature of personhood, we are drawing on the work of Margaret Somers (1994).

Interviews

Cynthia E. Harrison, Chair of NOW's Credit Task Force, interviewed by Greta Krippner in Washington D.C., August 24, 2010.
Deborah Ellis, Attorney for NOW LDEF, interviewed by Greta Krippner in Rutgers, New Jersey, February 8, 2017.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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